An Arabic Financial Sentiment Dictionary: Bilingual Corporate Disclosures and Market Reaction on the Saudi Stock Exchange

By

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Abstract

Arabic sentiment analysis is an emerging field compared to sentiment analysis in the English language. In the finance and accounting literature, the dictionary-based approach has been a widely recognized method for measuring textual sentiment. Additionally, finance-oriented sentiment dictionaries have been shown to be more accurate in capturing the textual sentiment compared to general-purpose dictionaries. As a result, Loughran and McDonald's (2011) finance-oriented dictionary has become a predominant tool for capturing textual sentiment across various English financial settings and has been mapped to other languages. The Arabic language, however, is regarded as low-resourced and morphologically complex, calling for specialized sentiment analysis tools suited to business communication. To date, no finance-oriented Arabic dictionary addresses textual sentiment in finance and business communication.

The research introduces an Arabic Financial Sentiment Dictionary, a robust Arabic sentiment dictionary designed for financial applications. The Arabic financial sentiment dictionary is constructed by translating the Loughran and McDonald (2011) dictionary into Arabic. The dictionary consists of Positive, Negative, and Uncertainty categories and is designed to address textual sentiment classification in financial narratives. The research evaluated the Arabic financial sentiment dictionary in cross-language settings, using 728 Arabic annual reports, 274 CEO letters, and their English counterparts from Saudi public firms. Additionally, the study evaluates the proposed dictionary against an Arabic general dictionary in capturing the sentiment in financial disclosures. The findings, consistent with those in the finance and accounting literature across languages, indicate that the Arabic finance-oriented dictionary is more accurate in capturing the tone of financial narratives, whereas general-purpose dictionaries often misclassify words in financial applications and include words that lack sentiment value.

The study further investigates the impact of machine translation on Arabic-English financial text, using a sample of annual reports and CEO letters from Saudi public firms. A growing body of literature employs machine translation to overcome the scarcity of available natural language pre-processing resources in low-resource languages, leveraging more suitable tools in other languages. However, the language pair in translation and the text's domain pose challenges to retaining the tone of the original text. To assess whether sentiment is preserved across Arabic and English financial disclosures, the study conducts a bidirectional translation experiment. The findings indicate that sentiment is largely preserved and that machine translation maintains relative intensity of sentiment, although positive language shows some discrepancies in the Arabic-to-English direction.

Lastly, using a sample of 686 firm-years of annual reports in Arabic and their corresponding English versions, the study examines whether tone (positive, negative, and uncertainty) in bilingual disclosures on the Saudi Stock Exchange is associated with returns differently following annual report releases. By applying an event study methodology, the findings reveal that tone in annual reports is associated with abnormal returns following their publication. In particular, negative tone across both languages is statistically significantly associated with lower cumulative abnormal returns, although the market's reaction is delayed. In contrast, positive and uncertain sentiments are neither informative nor statistically associated with returns. More importantly, the results indicate that the Saudi Stock Exchange responds similarly to the negative tone conveyed in the Arabic and English annual reports.

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Declaration of Authorship

I hereby declare that the work presented in this thesis reflects my own research and is submitted in fulfilment of the requirements for the degree of Doctor of Philosophy. All materials and resources used are acknowledged and properly referenced.

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Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Background and Context

Sentiment analysis or opinion mining deals with the textual context in terms of its meaning. Liu (2012, p.7) defines sentiment analysis or opinion mining as a field of study that examines “people’s opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes.” The work of sentiment analysis originated from computer science but over the years it has expanded to management and social sciences due to its importance to business and society (Liu, 2012). Textual analysis can be expressed in different terms, such as computational linguistics, information retrieval, natural language processing (NLP), or content analysis, all of which relate to text-based methods (Loughran & McDonald, 2011).

In financial markets, textual communication has become a crucial channel through which firms convey information and influence investors’ perceptions. Corporate reporting, including annual reports, CEO letters, press releases, and earnings calls, among others, contains narrative information that extends beyond numerical disclosures, providing insight into managerial confidence, risk perception, and trajectory. The availability of such textual data at a large scale has transformed financial communication into a valuable resource for empirical research.

The Saudi Stock Exchange (SSE) stands as the largest capital market in the Middle East and North Africa (MENA) region. In recent years, the government of Saudi Arabia has introduced several reform plans, such as Vision 2030, to transform the kingdom into a global financial hub. At the center of this transformation is the SSE, which has notably seen a substantial increase in the number of listed firms and in foreign investor participation. The Capital Market Authority (CMA), in an effort to liberalize the market, has relaxed the entry requirements for foreign institutional investors through the Qualified Foreign Investor (QFI) program. Furthermore, the corporate disclosures environment in the SSE has been strengthened through continuous legislative updates to ensure transparency and timely compliance. Saudi-traded firms are required to publish their annual reports in both Arabic and English, although Arabic prevails in legal matters.

1.2 Motivation for the Research

The growing field of financial textual analysis applies NLP techniques to gauge the tone and sentiment of corporate narratives. Prior studies, predominantly in the English language, have demonstrated that textual sentiment is linked to market reaction, such as abnormal returns, volatility, and trading volume. However, despite the advances in NLP resources for English, comparable tools for the Arabic language remain scarce. The linguistic imbalance restricts the research community from investigating textual sentiment in Arabic corporate communications. Arabic is a complex language from an NLP standpoint. Its rich morphology, complex inflectional system, diverse lexicon, and unique script present distinct challenges for computational processing, requiring NLP tools that specifically account for the characteristics of the Arabic language. Moreover, Arabic exhibits a high degree of linguistic polysemy; a single word may convey different meanings depending on the domain in which it appears, highlighting the importance of developing finance-oriented linguistic tools for Arabic financial analysis.

To date, there is no Arabic financial sentiment dictionary available to the research community for capturing sentiment in financial narratives. The importance of such resources for sentiment analysis in finance applications stems from the fact that finance-oriented dictionaries are designed and established to address sentiment interpretation with financial applications in mind. General sentiment dictionaries, by contrast, are inadequate for accurately capturing sentiment in financial narratives (Bannier et al., 2019; Loughran & McDonald, 2011, 2015; Henry & Leone, 2016). The Arabic language exhibits greater complexity than other languages, thereby requiring appropriate domain-specific resources.

The finance and accounting literature has demonstrated the explanatory power of textual sentiment in explaining market-related phenomena. However, the Arabic language has received little attention in empirical research on the role of textual sentiment as a proxy for explaining financial market behavior. Furthermore, because of globalization, firms in the SSE communicate through bilingual channels, using both Arabic and English. However, the consistency of tone across these communication channels remains unexplored.

Additionally, due to the scarcity of NLP resources, researchers rely on machine translation to transfer a corpus from a low-resource language to a high-resource language. These methods enable researchers to conduct sentiment analysis on the corpus using appropriate tools. However, machine translation is a challenging task, particularly when dissimilarities across language pairs are pronounced or when dealing with domain-specific text.

Arabic and English financial texts are often overlooked in sentiment preservation when applying machine translation.

1.3 Research Aims and Questions

The primary goal of this thesis is to develop an Arabic finance-oriented sentiment dictionary to assess textual sentiment within the context of Arabic financial narrative. The research examines the accuracy and implications of applying a general Arabic dictionary versus a finance-oriented dictionary in an Arabic financial textual context. Additionally, the study examines the degree of textual sentiment preservation across Arabic and English financial documents while evaluating the role of machine translation (MT). Lastly, the research aims to empirically investigate the bilingual tone across the Arabic and English corporate disclosures in the SSE market, and whether the textual sentiment identified across the two versions has explanatory power in subsequent market reaction. To accomplish the research aims, the following three questions guide the study:

1. To what extent does the proposed Arabic financial sentiment dictionary yield accurate results in measuring sentiment compared to Arabic general dictionaries?
2. To what extent does machine translation between Arabic and English affect the sentiment of financial disclosures?
3. To what extent does the Saudi Stock Exchange respond differently to textual sentiment in the Arabic and English annual reports?

1.4 Research Contribution

The research contributes to the Arabic sentiment analysis (ASA) and finance literature in several significant areas. First, the study contributes to the ASA and finance literature by providing a sophisticated financial dictionary established with financial applications in mind. The Arabic Financial Sentiment Dictionary (ArFinSD) is the first comprehensive and available finance-oriented dictionary for the research community. However, there have been minimal ASA studies on financial narratives, and most sources are unavailable to the research community. Furthermore, general Arabic dictionaries are typically the primary resource for ASA, and domain-specific dictionaries are scarce. The research, therefore, addresses this limitation by introducing the ArFinSD. This will enable financial researchers to move beyond quantitative measures and expand their analyses to test theories related to qualitative measures in Arabic financial narratives.

Second, the study contributes to the ASA and finance literature by providing evidence on the impact of MT on sentiment preservation when translating Arabic-English financial disclosures. The study offers insights into whether MT systems can retain sentiment when translating financial documents. The study's results are essential for researchers facing resource constraints in their target languages. Financial narratives require specialized tools to capture textual sentiment accurately, and MT systems may offer a valuable bridge to mitigate these limitations.

Lastly, the study contributes to the finance literature by providing evidence of the bilingual tone in the SSE market. The research applies a dictionary-based sentiment analysis approach to examine the tone in annual reports of 686 firm-years (2018-2023) from the SSE market. The study offers insights into how the market responds to the release of the annual reports. Empirical evidence on tone across Arabic annual reports and their English counterparts provides practical implications for local and foreign investors in informing their investment allocation decisions. Additionally, the study can help regulators and policymakers ensure transparency and accurate disclosure practices.

1.5 Structure of the Thesis

This thesis is organized into seven chapters. Chapter 1 introduces the research background and context, motivation, aims, research questions, and contribution. Chapter 2 reviews the relevant literature concerning the textual sentiment methodology, sentiment dictionaries, cross-language sentiment analysis (CLSA), and MT. Chapter 3 outlines the approach to constructing the Arabic sentiment dictionary, the design of the sentiment analysis for the research, and the validation methods across the sentiment analysis frameworks. Chapter 4 presents the financial corpus, NLP pre-processing, and methodological implementation of sentiment classification, as well as the proposed frameworks for preparing the sentiment analysis. Chapter 5 presents the results of the sentiment textual analysis and their discussion. Chapter 6 provides the empirical study of the SSE market reaction to bilingual tone. Chapter 7 concludes the thesis by summarizing the key findings, contributions, practical applications, practical implications, limitations, and future directions.

Chapter 2. Literature Review

2.1 Theoretical Background on Textual Sentiment in Finance

The emergence of behavioral finance has introduced ideas that challenge traditional finance. Whether the financial markets are efficient and market participants are rational has been a key controversial issue between behavioral and traditional finance. The efficient market hypothesis (EMH), introduced by Eugene Fama in the 1960s, posits that all available information in the market is fully reflected in market prices and all investors are rational. Behavioral finance researchers, however, have raised the role of market participants' behavioral and psychological aspects, arguing that people interpret information differently. Indeed, the concept of market rationality is questionable, considering the risk and uncertainty factors that financial markets present.

Furthermore, market irrationality can be observed in noise trade practices where investors make investment decisions based on behavioral biases. Trading on noise as if it were fundamental information ultimately affects prices and, more importantly, challenges market efficiency theory. Fama (1965) argues that irrational investors would trade against rational arbitrageurs in the market, leading to the cancellation of the trading noise effect or at least driving prices close to fundamental values. Nonetheless, behavioral finance researchers have consistently demonstrated the impact of behavioral and psychological factors on financial markets, such as overconfidence (Barber & Odean, 2001; Gervais & Odean, 2001), overreaction (De Bondt & Thaler, 1985), and loss aversion (Barberis et al., 2001). In addition to the behavioral criticism of the EMH, the theory has also been challenged by several inexplicable anomalies, such as the size effect, the January effect, and the calendar effect (Lo, 2007).

Another controversial assumption, according to the EMH, is information efficiency, which indicates that any new information related to the market will fully and quickly be reflected in stock prices. The concept of information efficiency has been the core objective in many finance studies. Without doubt, information is the most valuable asset in financial markets for both the demand and supply sides and, more importantly, the rate of information flow is directly related to market activities such as trading volume and return volatility (Vlastakis & Markellos, 2012). However, information is not always available to everyone simultaneously and information related to the financial markets takes different forms, thereby affecting the demand side. Investors do not allocate equal attention when processing quantitative and qualitative information (Li, 2006).

A substantial body of the finance literature has focused on quantitative factors in an attempt to explain and better understand financial events. Quantitative data are more objective, easily accessible and, more importantly, less controversial than qualitative data (Feldman et al., 2010). Nevertheless, textual information is more costly to analyze. For instance, the annual reports provided by US public companies contain, on average, 70,279 words, which require more effort to extract the data they contain (Li, 2006). Additionally, financial market participants cannot make investment decisions solely based on quantitative information. Shiller (1981) and Cutler et al. (1989) are examples of early studies that realized the importance of qualitative data in the finance literature. Furthermore, the importance of qualitative information has increased over time as corporate transparency and governance principles have increased (Feldman et al., 2010).

Understanding the narrative financial content reduces the information asymmetry gap between market participants, leading to better investment decisions. Despite the complexity of analyzing textual information in corporate disclosures, managers have more power in narrative disclosures than in numeric data. Depending on the firm's performance, managers may use tone management to mislead investors by being inordinately positive or negative relative to the reported quantitative information (Huang et al., 2014). By contrast, quantitative data are usually strict and subject to general accounting principles. In addition, not only are corporate financial disclosures, such as annual reports, press releases, and earnings releases, prepared by insiders who have a better knowledge of the firm's performance, but qualitative information gathered from corporate disclosures can also be critical because they may offer incremental information regarding the firm's future performance. That is because narrative information of corporate disclosures contains forward-looking information, whereas nearly all numbers in financial statements are historical and backward-looking values (Li, 2006).

Within the sentiment literature, behavioral finance researchers have studied sentiment from two perspectives: investor sentiment and textual sentiment (Kearney & Liu, 2014). Investor sentiment can be defined as a belief about future cash flows and investment risks that are not justified by fundamental values or the facts at hand (Baker & Wurgler, 2007). Researchers in this field have employed a range of sentiment proxies to measure investor sentiment, including investor mood (Edmans et al., 2007; Wang & Markellos, 2018) and retail investor trades (Greenwood & Nagel, 2009; Kumar & Lee, 2006). The second type of sentiment is referred to as textual sentiment, which measures the degree of positivity to negativity in texts. The measurement scale can further include other classifications, such as strong, weak, and uncertain. The fundamental difference between investor sentiment and textual sentiment is that the former reflects investor behavioral characteristics, whereas the latter may include the former but reflects conditions within markets, firms, and institutions (Kearney & Liu, 2014). Importantly, Kearney and Liu (2014) note that behavioral finance researchers avoid making any assumption related to the connection between textual sentiment and investor sentiment. However, textual sentiment analysis has been a critical approach used to understand and explain essential events in the market and its aspects. Moreover, textual sentiment analysis was conducted by relying on three information sources: corporate disclosures, media articles, and internet messages (Kearney & Liu, 2014). Each type of information has been examined and tested to explain various financial events, and researchers have found profound evidence of the relationship between textual sentiment and market reactions.

2.2 Textual Analysis Methodologies in Finance

2.2.1 Dictionary-Based Approach and Word Lists

The most commonly used content analysis methods in the textual sentiment literature are the dictionary-based approach and machine learning (Kearney & Liu, 2014). The dictionary-based approach employs a mapping algorithm that classifies words, phrases, or sentences into distinct categories based on predefined dictionaries (Li, 2010). In other words, the dictionary-based approach employs a 'bag-of-words' (BOW) technique to classify words according to predefined positive, negative, or uncertain categories. A widely used dictionary in sentiment analysis is the Harvard University General Inquirer (GI) IV-4 dictionary, a well-known quantitative content analysis program developed by Philip Stone (Stone et al., 1966). As Pennebaker et al. (2003, p.550) note, "The General Inquirer (GI) is generally considered the 'mother' of computerized text analysis." The GI applies the Harvard IV-4 Psychosocial Dictionary, which has 77 categories and approximately 12,000 words. Additionally, the GI dictionary was developed with a focus on political science, literary criticism, and social psychology (Stone et al., 1966). However, a considerable amount of the literature in financial sentiment analysis has employed the GI/Harvard dictionary to measure various financial narratives.

Using the Harvard IV-4 Psychosocial Dictionary, Tetlock (2007) was among the first researchers to provide positive evidence of the interactions between news media content and stock market activity. Tetlock found that a heightened level of journalistic pessimism in the daily column leads to lower returns the next day. Following the same method that Tetlock

(2007) used, which counts the number of negative words as predefined in the Harvard Psychosocial Dictionary, Engelberg (2008) measured differential information processing costs in the context of earnings announcements. He illustrated the positive relationship between linguistic media content and the stock market. Nonetheless, Engelberg questioned the accuracy of Harvard's positive words within financial disclosures. Similarly, other studies have employed the Harvard Psychosocial Dictionary, including Kothari et al. (2009), Henry and Leone (2016), and Doran et al. (2012).

Another extensively used general dictionary in the accounting and finance literature is the Diction dictionary. The Diction dictionary textual analysis software was developed by Roderick Hart, a specialist in mass media politics (Kearney & Liu, 2014). The Diction dictionary classifies words as optimistic and pessimistic, contains 35 predefined dictionaries, and is based on 10,000 words (Pennebaker et al., 2003). Davis and Tama-Sweet (2012) utilized the Diction dictionary to examine managers' tone in narrative disclosures, specifically management's discussion and analysis (MD&A), a subsection in annual reports, and earnings press releases. They report that higher levels of pessimism in the MD&A lead to lower future returns on assets. Similar implications of the association between optimistic language in earnings press releases and future returns on assets are reported by Davis et al. (2012). The Diction word list has also been employed in the financial literature, including by Henry and Leone (2016), Rogers et al. (2011), Ferris et al. (2013), and Loughran and McDonald (2015).

Despite the widespread use of general dictionaries in financial settings, several researchers have raised concerns about the English language's polysemy. Driven by the question of whether general dictionaries, which are widely used by psychological researchers, are appropriate to apply in the financial discipline, Henry (2008) created the first specific finance-word list to capture the sentiment tone in earnings press releases. Henry's list of 'domain-relevant' words contains 85 negative words and 104 positive words and was created using quarterly earnings announcement-specific terminology. The author reported that the initial market reaction can be affected by the tone of the earnings announcement. Henry also argues that the Harvard IV-4 Psychosocial Dictionary is too broad to be applicable in financial contexts.

Henry and Leone (2016) emphasize that in a financial disclosure setting, Henry's word list is more powerful than a general word list such as the Diction dictionary. Several studies have utilized Henry's (2008) word list. For instance, Price et al. (2012) examined the earnings conference calls for publicly traded companies and the corresponding market reaction. They report that Henry's dictionary is much more powerful and more accurate in capturing the tone of earnings conference calls compared to the Harvard IV-4 Dictionary. The scarcity of finance content-specific dictionaries continues to encourage scholars to look beyond general dictionaries.

In 2011, Loughran and McDonald developed a unique dictionary for the finance discipline. The LM dictionary comprises six distinct sentiment categories: negative, positive, uncertainty, litigious, strong modal, and weak modal. The initial purpose of the LM dictionary was to examine word usage in annual reports. Their dictionary is based on words that appeared in at least 5% of the annual reports filed by US public companies between 1994 and 2008. More importantly, a part of their analysis focuses on the MD&A, where management may reveal information regarding tone and sentiment. The authors emphasize that general dictionaries, such as the Harvard Psychosociological Dictionary, could provide misleading results in terms of word classifications in financial settings. In fact, by using a BOW method, they find that 73.8% of the Harvard Dictionary's negative words are not necessarily negative in the financial discipline. For instance, words such as 'liability,' 'tax,' 'cost,' 'capital,' and 'board' have different meanings and implications when applied in a financial context. That is simply because English words have different meanings depending on the discipline and its own specific dialect. Similarly, they reported in a later study that 83% of negative words and 70% of words found in the Diction list are misclassified (Loughran & McDonald, 2015).

Although the Henry list and LM word lists were developed with financial communication in mind, notable differences exist between them. The Henry word list was designed to assess managers' tone in earnings press releases, whereas the LM word lists were created to examine the usage of words in annual reports. More critically, the LM word lists are more comprehensive. For instance, the most frequently used negative words in the LM word lists, such as *against*, *adverse*, *restated*, *adversely*, *restructuring*, *loss*, *losses*, *claims*, *impairment*, and *litigation*, are not included in the Henry word list (Loughran & McDonald, 2016). Therefore, the LM dictionary has been employed to measure sentiment in other financial narrative contexts beyond its initial purpose, including news articles (Garcia, 2013), earnings-related conference calls (Davis et al., 2015), IPO prospectuses (Ferris et al., 2013), and mutual fund shareholder letters (Hillert et al., 2025). The LM dictionary has attracted researchers in the finance literature and has become increasingly dominant in recent studies (Kearney & Liu, 2014).

2.2.2 Alternative Approaches for Sentiment Classification

An alternative approach to capturing the textual sentiment in financial narratives is the machine learning method, which mathematicians and computer scientists initially introduced. Machine learning methods begin by manually categorizing a proportion of the entire corpus of text documents into various sentimental categories known as a training set. Subsequently, sentiment analysis algorithms such as naïve bayes (NB), support vector machine (SVM), or neural networks apply the classification rules created or ‘learn’ from the training set (Li, 2010). Researchers have employed machine learning methods in various financial settings to examine the impact of sentiment.

As one of the earliest studies to apply the NB algorithm, Antweiler and Frank (2004) investigated the effect of over 1.5 million internet stock messages from Yahoo! Finance and Raging Bull on returns, trading volume, and volatility. They reported that stock messages have a statistically significant effect on stock returns and message posting helps to predict volatility. Similarly, Li (2010) applied the NB algorithm to examine the tone of 13 million forward-looking statements (FLS) from more than 140,000 10-Q and 10-K filings from 1994 to 2007. He found that the positive tone of FLS is positively correlated with future earnings. Das and Chen (2007) developed a machine learning method by applying various classification algorithms that help extract small investor sentiment from stock message boards. They reported that small investor sentiment and message activity are related to market activity. Buehlmaier and Whited (2018) investigate the impact of tone in the MD&A section of annual reports on stock returns, assessing whether financial constraints affect stock returns. The authors demonstrated that financially constrained firms have higher stock returns. Similar to the dictionary-based approach, machine learning methods have been employed in the finance literature to analyze sentiment in various information sources, including corporate disclosures, news media, and internet messages.

Recently, computational linguistics researchers have introduced deep-learning-based algorithms capable of learning the semantic and syntactic relationships between words, enabling more accurate textual classification. Examples of language models include the Generative Pre-Training model (OpenAI GPT) (Radford et al., 2018), the Bidirectional Encoder Representations from Transformers (BERT model) (Devlin et al., 2019), and Embeddings from Language Models (ELMo) (Peters et al., 2018). These models, known as large language models (LLMs), rely on large amounts of text (up to billions of tokens). Although LLMs differ in their architectures and training methodologies, they fundamentally rely on predicting the next word's probability distribution in a given text based on previous words. Therefore, LLMs are equipped to encode both syntactic knowledge and semantic knowledge (Rogers et al., 2020). Deep learning algorithms rely on training data to learn multiple linguistic features, enabling the model to capture the passage's structure, context, and meaning. Learning the semantic aspects of the language is beneficial in sentiment classification, where negation and longer-range word associations are prevalent in textual data.

LLMs, such as the BERT model, require fine-tuning to meet the needs of various NLP tasks and domain-specific classification with several modifications. For example, Huang et al. (2023) introduced a large language model (FinBERT) based on Google's BERT algorithm to capture the sentiment of financial texts. In their study, they pre-trained a collection of unlabeled financial texts, including annual reports, analyst reports, and earnings conference call transcripts. The total size of their sample was 5.9 billion tokens, significantly more than the 3.3 billion tokens that Google utilized to pre-train the original BERT model. Subsequently, they fine-tuned the model based on 10,000 labeled sentences that early studies classified to measure the sentiment of earnings conference call transcripts. They explored eight classification algorithms, including a dictionary-based approach (LM dictionary). Although FinBERT achieved a better accuracy rate than the dictionary-based approach, the LM dictionary was positively associated with market reaction, particularly in explaining cumulative abnormal returns.

2.2.3 Comparison of the Dictionary-Based Approach and Alternative Approaches

The dictionary-based methodology has its advantages and disadvantages relative to the alternative textual analysis approaches, such as machine learning algorithms or LLMs. The dictionary-based approach relies on predefined dictionary categories or word lists. Because there are well-established dictionaries such as the Harvard-IV-4 Psychosocial Dictionary and Diction dictionary, the dictionary-based approach is easier, less expensive, and more time-efficient for financial analysts to employ (Kearney and Liu 2014). This is due to the effort required to fine-tune or build the training set for these alternative approaches. Furthermore, researchers with little knowledge of the subject or the language of the text being analyzed can easily apply the dictionary-based approach. Additionally, because the dictionary-based approach relies on a predefined dictionary, the researcher's subjectivity is minimized and the analysis can also be easily replicated by other researchers (Loughran & McDonald, 2016).

To that end, because the word's polarity is pre-classified based on its corresponding sentimental category, the classifier accuracy does not require further validation. However, machine learning algorithms require additional steps to assess the quality and accuracy of the classifier. These models require manual annotation, also referred to as data labeling in the literature. At this stage, a field expert classifies the data in terms of whether it is a sentence, a paragraph, or a subsection and assigns it to its corresponding fitted sentiment group (up to 80% of the data). Subsequently, a small proportion of the annotated data, known as out-of-sample, is tested regarding the classification accuracy of the algorithm, usually measured by the Macro-F1 score[1]. This validation method is known as the train-and-test approach, which evaluates the classifier's effectiveness. It is worthy of note that there are other methods for assessing classification accuracy, such as training error or N-fold cross-validation (Li, 2010).

Consequently, the data annotation process can lead to classification bias, whereby two annotators disagree regarding the labeling process. For example, Das and Chen (2007) reported a 72 percent agreement score between human coders regarding their training sample. This is especially crucial in the Arabic language, given the dialectal differences among Arabic speakers. In the NLP Arabic literature, it is common to involve up to three experts in the annotation process and test the agreement score among the classifications. These steps require time and expertise in the field of study to achieve a high degree of accuracy. In contrast, the researcher's subjectivity is avoided when using a predefined sentiment dictionary (Loughran and McDonald, 2016).

Along the same lines, Henry and Leone (2016) conducted a study comparing machine learning and dictionary-based sentiment measures using forward-looking statements in MD&A. In their research, they used the NB algorithm and the LM dictionary. They reported slight differences between sentiment measurement results, favoring the dictionary-based approach because it is much easier to apply, replicate, and interpret. The replication difficulties are not only due to inconsistencies in how experts label the training data across different studies but also to algorithm results, which are inherently associated with the training dataset (Henry & Leone, 2016). Given that machine-learning algorithms incorporate different research design choices, such as the validation process methods, two studies may produce different results even if they agree on the sentiment classifier algorithm. The dictionary-based method, however, is more accurate in terms of producing identical results across different studies. For instance, Frankel et al. (2022) applied the LM dictionary to test the market reaction around 10-K filing

[1] This metric is widely employed in the natural language processing literature to evaluate the performance of a prediction algorithm.

dates, relying on the same dataset and the original study period as Loughran and McDonald (2011) and confirmed the former's results.

Although advanced models may outperform traditional machine learning algorithms or dictionary-based approaches in terms of sentiment analysis accuracy in finance (e.g., see Huang et al., 2023; Siano & Wysocki, 2021; Azimi & Agrawal, 2021), they pose several challenges. Initially, LLMs require a considerable amount of textual data and computing resources, which are complex and costly to train. This is because a vast number of parameters are crucial in building LLMs. Consequently, the implementation cost is very high due to the need for computing resources, including cloud servers, graphics processing units (GPUs), storage, high-capacity processors, and the required energy. These requirements are necessary to train the models to reach a high level of performance. The implementation cost, both financial and environmental, of developing these models has been a subject of debate in several studies, questioning whether these costs are justified and necessary (Strubell et al. 2019; Schwartz et al. 2020; Bender et al. 2021). From a financial perspective, the computing resources required for these models are only available at the labs of leading technology companies. This potentially hinders the academic community's ability to build and train LLMs to test various research questions. For example, the hardware needed to develop the model in Strubell et al.'s (2019) study cost US$145,000, plus electricity (approximately 58 GPUs for 172 days).

Furthermore, alternative approaches to sentiment classification require data annotations, which are used to either fine-tune LLMs or train machine learning classifiers to align these models with the targeted domain. This step involves a large amount of labeled data, which may be unavailable or difficult to obtain. For example, Frankel et al. (2022) and Siano and Wysocki (2021) utilized firm fundamentals as an alternative to sentiment labeling for their machine learning algorithms. Nonetheless, the use of alternative sentiment indicators, such as stock market performance measures or accounting variables, has not been thoroughly studied in terms of classification accuracy compared to human or expert labeling references. Additionally, past performance may not accurately reflect current sentiment because textual sentiment generally provides better forward-looking anticipatory signals than the reported performance from previous periods. As noted by Huang et al. (2023), although weakly supervised learning algorithms can reduce the cost of manual data labeling, they compromise accuracy.

Another challenge associated with using LLMs for financial sentiment classification is their complexity, which makes them challenging to interpret and replicate. Given that large models rely on billions of parameters, it is difficult, if not impossible, to trace how the trained model turns inputs into outputs (Huang et al., 2023). The lack of interpretability in these models limits the ability to pinpoint the influence of specific words or phrases for predicting sentiment in financial disclosures. The opacity in these LLMs is referred to as 'black boxes' in computational linguistics, which stems from the fact that the machine cannot explain or demonstrate how it converts an input into an output. Loughran and McDonald (2016) emphasize that the limited interpretability of machine learning models poses a barrier to academics employing them to test economic theories.

These limitations associated with alternative sentiment classification models, despite rapid advances, make the dictionary-based sentiment analysis approach a valuable and easy-to-use 'on the shelf' tool for gauging textual sentiment in financial narratives. Relying on a sentiment dictionary with a specific orientation enables academics to replicate and apply the dictionary to investigate a variety of hypotheses. Hence, scholars have employed the LM dictionaries and reported a positive association between textual sentiment and market reactions. Although the LM dictionary was constructed using 10-K financial reports, further studies investigate various financial textual data. For example, studies use the LM dictionary regarding initial public offerings (IPOs) (Guo et al., 2022; Jegadeesh & Wu, 2013; Loughran & McDonald, 2013), financial news (Engelberg et al., 2012; Ferguson et al., 2015; Garcia, 2013; Liu & McConnell, 2013), social media (Chen et al., 2014), and earnings press releases (Henry & Leone, 2016). The extensive use of the LM dictionary is partly due to the flexibility of the dictionary-based approach in testing various financial theories.

2.3 Non-English Dictionaries

The majority of dictionary-based analyses in finance are conducted using English resources. For other languages, the most frequently used dictionaries are typically general English dictionaries that have been adapted for use in those languages. For example, the Linguistic Inquiry Word Count (LIWC), which was developed to measure psychometric properties, has been translated into numerous languages, including German, Spanish, Norwegian, Portuguese, Dutch, and Italian. Other languages are also under development, including Arabic, Korean, Chinese, and Turkish (Pennebaker et al., 2015). However, a few non-English general language dictionaries are available for several languages, such as Japanese (Kaji & Kitsuregawa, 2007), Spanish (Molina-González et al., 2013), and Chinese (Tan & Zhang, 2008). Nonetheless, general dictionaries are unsuitable for capturing sentiments in finance-specific contexts.

Researchers have proposed new approaches to measure sentiment and subjectivity, such as bilingual dictionaries, parallel corpora, or CLSA, to overcome the scarcity of appropriate general dictionaries in other languages. One such approach is to rely on translating non-English documents into English using commercial MT services and then applying sentiment analysis using English dictionaries (Bannier et al., 2019). For example, due to the limitations of sentiment analysis in other languages, Wan (2008) and Brooke et al. (2009) conducted sentiment analysis by translating documents from Chinese and Spanish, respectively, into English using online MT services. Wan (2008) argues that analyzing translated documents offers superior performance relative to analyzing them using Chinese resources. He also emphasizes that the analysis can be improved by combining the results in different languages. However, Brooke et al. (2009) highlight that analyzing translated documents leads to a significant semantic loss, especially for the original text.

More importantly, specific-domain dictionaries have also attracted researchers to measure sentiment in different languages. González et al. (2021) conducted a sentiment analysis of Spanish and Portuguese contexts by measuring the tone in the president's letter, a subsection of the annual report, using the LM dictionary. González et al. (2021) utilized three dictionaries to account for the differences between languages and relied on a language translator to convert the LM dictionary to Spanish and Portuguese. They further validated their translations using a sample of three language versions of financial news from Bloomberg and estimated the correlation to be approximately 0.7 or higher. Driven by a similar motivation, Bannier et al. (2019) developed a specific German business dictionary by adapting the LM dictionary. Their sample comprised 1,402 quarterly and annual reports of stock-listed companies available in both English and German versions. They initiated the adaptation process with a word-by-word translation to German, taking into account several critical linguistic aspects, including grammatical features, compound wording, and lexical morphology.

Although both studies relied on the LM dictionary, several drawbacks are apparent. González et al. (2021) developed a joint dictionary of the Spanish and Portuguese languages but they did not clarify which language translator they employed nor did they describe how they addressed the morphological differences and synonyms of the two languages. Furthermore, the authors did not provide any further robustness checks or mention any possible biases because they rely on automated translation, which has been described as delivering semantic losses. Unclear processes hinder the replicability of their approach and the dictionary is not publicly available. In response to this criticism, Bannier et al. (2019) offer a more detailed process for adapting the LM dictionary, arguing that their approach is more comprehensive and can serve as a framework for similar dictionary adaptations in other languages. Hence, they provide an extensive description of the adaptation setup in a detailed manner. For example, they raise the issue of different language aspects, such as inflectional words. In addition, they test the dictionary's quality and ability to capture market-relevant textual sentiment by comparing it to general dictionaries, such as the Harvard Dictionary. The authors further compare their dictionary-based approach to a machine-learning approach.

2.4 Arabic Dictionaries

ASA has received less attention and remains in the early stages compared to textual analysis carried out on English texts. Arabic text can be expressed in two different types:[2] Modern Standard Arabic (MSA) and colloquial or dialectal Arabic (DA). MSA is primarily used in formal communication channels, including corporate disclosures, news outlets, and educational settings. In contrast, DA, a spoken and informal language, is used in daily communication and on social media platforms. Furthermore, each region of the Arab world has its own dialect and certain words can have completely different meanings depending on the dialect. As a result, textual analysis researchers have focused on one of the Arabic language types or, in most cases, a combination of MSA and specific regional dialects. According to a comprehensive systematic literature review of ASA by Ghallab et al. (2020), analyzing both MSA and DA is a more dominant trend than analyzing either MSA or DA alone. This is because most studies are based on data resources collected from social media and microblogging channels (Ghallab et al., 2020).

The process of analyzing Arabic text is more challenging than that of other languages, such as English, for several reasons. First, Arabic is more complex due to its highly morphological and inflectional aspects. Second, capitalization is absent in Arabic, which indicates difficulties in identifying acronyms, abbreviations, or names. Third, the direction of writing is from right to left and, more importantly, the shape of the word changes depending on the word's location in the sentence. Despite these linguistic issues, the Arabic language lacks proper Arabic dictionaries and only a few are publicly available to the research community.

To overcome the scarcity of available Arabic sentiment dictionaries, researchers have made a significant effort to develop Arabic language resources. More importantly, a substantial

[2] Scholars in Arabic NLP further distinguish Classical Arabic (Qur'anic and pre-modern religious texts) as a third type of Arabic text.

body of ASA literature has been conducted with general-purpose applications in mind. As an early pioneering work to establish large-scale lexicons, Abdul-Mageed and his colleagues created several large-scale subjectivity and sentiment lexicons considering the different types of the Arabic language. For instance, Abdul-Mageed et al. (2011) created a polarity lexicon containing 3,982 Arabic adjectives labeled as positive, negative, or neutral. In a subsequent study, Abdul-Mageed and Diab (2014) introduced SIFAAT, an Arabic sentiment lexicon based on the news domain, comprising 617 positive, 550 negative, and 2,158 objective categories. Furthermore, the authors created the HUDA, a dialect lexicon of Egyptian DA, consisting of 4,905 entries extracted from the Egyptian Yahoo Maktoob chat room. Similarly, Elhawary and Elfeky (2010) created an Arabic lexicon that contains 1,600 words (600 positive, 900 negative, and 100 neutral) for mining Arabic business reviews. Mahyoub et al. (2014) developed an Arabic sentiment lexicon comprising 2,000 words (800 positive, 600 negative, and 600 neutral words) based on Arabic WordNet (AWN)[3]. Meanwhile, Badaro et al. (2014) utilized a combination of different lexicons, including AWN, English SentiWordNet[4] (ESWN), and SAMA[5], to construct a large-scale Arabic sentiment lexicon (ArSenL). Their version covers 28,760 lemmas and 157,969 synsets.

Similarly, Eskander and Rambow (2015) developed another large Sentiment Lexicon for Standard Arabic (SLSA), comprising 35,000 lemmas and POS combinations, to address deficiencies in existing Arabic resources. Its construction involves linking the AraMorph morphological analyzer to SentiWordNet to retrieve sentiment scores for four parts of speech: nouns, verbs, adjectives, and adverbs. Al-Moslmi et al. (2018) utilized MPQA[6], an English subjectivity lexicon, and two other Arabic review corpora to create an Arabic sentiment lexicon comprising 3,880 positive and negative synsets, corresponding to 13,760 positive and negative words. Furthermore, the authors created a multi-domain Arabic sentiment corpus (MASC). The corpus comprises 8,860 positive- and negative-labeled reviews from 15 sentiment domains, with the financial services domain comprising 100 positive and 50 negative reviews. Nevertheless, these sentiment dictionaries are designed for general usage applications and are unsuitable for capturing textual sentiment in the realms of Arabic business and finance.

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[3] AWN was originally an English lexical resource that has been expanded and adapted into Arabic. It contains words, synsets, and semantic relations such as antonymy, synonymy, and meronymy.

[4] ESWN is an English sentiment lexicon that has been employed to map English resources into Arabic and applied to a variety of ASA applications (e.g., Badaro et al. 2014; Eskander & Rambow 2015).

[5] SAMA is a commonly used tool for the morphological analysis of Standard Arabic. https://catalog.ldc.upenn.edu/LDC2010L01

[6] MPQA is a subjectivity lexicon compiled by expanding a list of subjectivity clauses using several sources, including the General Inquirer (Wilson et al., 2005).

In terms of ASA in financial settings, there have been only a few attempts to capture sentiment using various approaches. For example, Al-Rubaiee et al. (2015) investigated the impact of social media platforms, namely Twitter, on the Saudi financial market. Using a machine learning approach, they manually classified 1,943 tweets from Mubasher, a stock analysis software provider, and developed a list of over 40 financial words and idioms. Subsequently, they expanded their analysis to include more financial terms (Al-Rubaiee et al. 2017). The expanded list covered more than 100 financial terms and expressions and was divided into two categories: positive and negative. Although the authors found a correlation between sentiment in tweets and the Saudi financial market, their analysis had several drawbacks in terms of its scope. Both the corpus and dataset were very small and most of the data were used to develop the training set. Moreover, it is challenging to replicate their analysis in formal financial settings, such as annual reports or earnings press releases, because the training set was based on a social media platform where participants use Arabic colloquialisms. Motivated by the same question of whether Twitter posts directly influence the Saudi stock market, Alenezi and Qureshi (2018) conducted a similar analysis and found a strong correlation between sentiment and stock market trends.

In a more comprehensive study, Alkhatib et al. (2016) investigated the relationship between Twitter posts and stock market reactions. The dataset was compiled from six different stock market indices, comprising approximately 1.1 million tweets. The authors employed the SentiStrength tool, a general English sentiment lexicon adapted for use with other languages, including Arabic, to measure the ability of Twitter Arabic content to predict movements in stock markets. Their results indicate different degrees of association between sentiment and market reaction across the six markets. The Egyptian index is positively correlated, whereas the Saudi and Kuwait indices are less correlated. However, the authors do not address the potential bias associated with using automated translation nor the use of a general dictionary for finance-related content. Furthermore, they only reported a correlation test to validate their results. It is worthy of note that social media platforms and microblogging channels are the primary data sources for ASA in the finance field. More importantly, to the best of the researcher’s knowledge, there is no comprehensive Arabic sentiment dictionary that captures and analyzes financial narrative information.

2.5 Islamic Finance

Arabic is the mother language of Islamic finance which has expanded rapidly since the early 2000s. Hence, following the financial crisis (2007-2009) and the European sovereign debt crisis of 2011, scholars shifted their attention to the so-called faith-based financial system which has demonstrated steady and significant growth. According to the Islamic Financial Service Industry Report (2019), total Islamic financial assets have increased dramatically from US$150 billion in the mid-1990s to US$2,000 billion by the end of 2019. Furthermore, the Arabic region hosts the vast majority of Islamic financial assets. Based on Islamic finance theory, firms that comply with Sharia principles are subject to several restrictions, which are fundamentally based on the guidance of the Holy Quran and the traditions of the Prophet Mohammad (Sunna). More importantly, Islamic finance relies on specific terminologies that are unique and difficult to translate without reference to the context because most modern Islamic financial instruments originate from classical religious texts. For example, a *Mudarabah* contract refers to a business contract in which one party provides the capital and the other puts in the effort with no obligations in the event of a business loss. However, the word Mudarabah in a general context has an entirely different meaning.

The practical implications of Sharia compliance for firms have been extensively investigated from various dimensions, including equity market performance, Islamic bonds, asset pricing, market interactions, and ethical issues in Islamic finance. Nevertheless, in the Islamic finance literature, the majority of sentiment analysis studies focus on investor sentiment rather than textual sentiment. Specifically, religious occasions have been widely used as a proxy to measure sentiment and its impact on financial markets (Bialkowski et al., 2012, 2013; Abbes & Abdelhedi-Zouch, 2015; Jaziri & Abdelhedi, 2018). However, textual sentiment analysis of the Arabic Islamic financial context is rare.

2.6 Machine Translation and Cross-Language Sentiment Analysis for Arabic Financial Texts

The resources available for sentiment analysis in many languages, including Arabic, are often lacking. These resources, including sentiment dictionaries, corpora, and pre-processing tools, are essential for sentiment analysis. To overcome the scarcity of resources, researchers have relied on alternative approaches, including transferring resources to rich-resource languages, which can be classified as CLSA. Furthermore, MT technology has undergone incremental developments, leading many researchers to incorporate MT into sentiment analysis projects in various languages. MT serves as a bridge and an alternative method for conducting sentiment analysis that involves translating the target language (a resource-scarce language) into a resource-rich one, such as English. This method enables scholars to utilize a more extensive range of resources available for sentiment analysis.

Consequently, several sentiment analysis studies across multiple languages, including Arabic, have relied on English sentiment resources. The primary motivation behind these studies is the scarcity of resources focused on sentiment analysis in targeted languages. However, relying on MT for sentiment analysis may lead to a reduction in accuracy and a potential loss of sentiment. Among the various tasks in NLP, MT is recognized as the most challenging (Wang et al., 2022). Furthermore, the effectiveness of MT systems is heavily dependent upon the languages involved in the translation process, commonly referred to as the language pair. The challenge is particularly apparent when analyzing a language pair such as Arabic-English, where significant structural, semantic, and morphological differences exist (Zakraoui et al., 2020; Mohammad et al., 2016). Therefore, the linguistic accuracy of MT systems becomes crucial in CLSA.

2.6.1 Machine Translation Advances

The origins of MT date back as early as 1949, when Warren Weaver proposed the initial concept of MT using a computer (Wang et al., 2022). Since then, the evolution of MT technology has gone through significant developments. The advancement of MT approaches began with the rule-based method, followed by the corpus-based method, and has recently advanced to neural machine translation (NMT). From the early development of MT to the 1990s, rule-based approaches were the dominant methods used in MT which rely on bilingual dictionaries and manually written linguistic rules to translate the source language into the target language (Wang et al., 2022). Shortly afterwards, due to the difficulty in maintaining written linguistic rules and replicating these rules for other languages, rule-based methods were replaced by corpus-based methods (Wang et al., 2022). Corpus-based methods, including statistical machine translation (SMT) and NMT, rely on bilingual parallel corpora, whereby various techniques are employed to align raw textual data with their translations. A substantial amount of parallel data with high equivalence across the languages is used to attain accurate and reliable translations using the corpus-based method. The emergence of NMT marked a significant milestone in the field of MT, which caused a sudden shift in the direction of mainstream research (Stahlberg, 2020).

Despite rapid advances in MT in recent years, the issue of MT accuracy remains a dominant subject of research in the field of NLP, not only for Arabic but also for other languages. MT involves analyzing linguistic aspects in both the source and target languages, including semantics, syntax, morphology, and other grammatical categories. Additionally, the MT task is further exacerbated in languages where the source and target languages exhibit significant linguistic differences, as in the case of Arabic-English MT (Zakraoui et al., 2020).

The complexity of the Arabic language and recent developments in MT have encouraged several studies to conduct evaluation assessments of MT systems, such as Google Translate[7], Microsoft Translate[8], and other free online systems. Additionally, online MT systems vary in terms of their effectiveness due to the diverse approaches employed in these systems. Online MT systems often use a combination of linguistic rules and methods, making it crucial to evaluate the quality of translation output rather than the technique upon which the system is built.

Generally, two approaches are used to assess the quality of a translation: manual (human) evaluation and automatic evaluation (e.g., Bilingual Evaluation Understudy (BLEU)[9], Error Analysis, F-measure), or a combination of both. Traditionally, the assessment of MT systems has emphasized linguistic accuracy rather than task-specific performance. In the Arabic-English context, several studies have contributed to assessing the translation qualities without considering the downstream application. Additionally, among the most widely evaluated online MT systems in the Arabic MT literature are Google Translate and Microsoft Bing Translate. This is unsurprising because these two translation engines have become the default choice of translation tools for individuals seeking quick and accessible translations (Almahasees, 2021).

To that end, in the Arabic language, studies concerning MT evaluation continue to provide inconsistent accuracy verdicts in their MT assessments (Hadla et al., 2014; Harrat et al., 2019; Ameur et al., 2020; Ali, 2020; Almahasees, 2021; Banimelhem & Amayreh, 2023). In MT accuracy assessment studies, what constitutes a highly accurate translation is the MT model that comes closest to 'the gold standard' traditional human translation. Despite advances in recent NMT systems which have demonstrated better performance than conventional SMT systems for Arabic, it can be argued that these models still fall short in specific linguistic

[7] https://translate.google.com
[8] https://www.bing.com/translator
[9] The BLEU score metric is among the most employed methods in evaluating machine-translated text in the Arabic language. 60% BLEU scores and above are interpreted as high quality translation and often better than human. For more details, visit: https://cloud.google.com/translate/docs/advanced/automl-evaluate#bleu

contexts. A major contributor to this phenomenon is that the Arabic language introduces linguistic obstacles that affect the MT process. For instance, Arabic word ambiguity, known as word polysemy, presents an obstacle to the MT system. This is because Arabic words can have different meanings based on their context. This is a common challenge in Arabic, particularly when dealing with Arabic dialectal textual data. For example, the word رهيب can be interpreted as ‘terrible’ in MSA or ‘great’ in Arabic dialect. Arabic dialects are widely considered to be one of the most persistent challenges, not only for MT systems but across all Arabic NLP applications.

Furthermore, the absence of vocalization marks or diacritical characters further hinders the precision of MT systems, especially when processing short texts with limited context (Ameur et al., 2020). For example, the word مال without diacritization can be interpreted as مالُ, which is a finance-related term referring explicitly to ‘money.’ However, the same word can serve as a verb indicating an unrelated term, مالَ, which means ‘to lean.’ Another example of finance-related terms in Arabic is نَقْدٌ and نَقَدَ, where the former refers to ‘cash’ or ‘money’ and the latter refers to the past tense verb ‘he criticized.’ In the Arabic language, a text can be fully diacritized, partially diacritized, or entirely undiacritized, which introduces various pre-processing challenges to Arabic NLP applications (Habash & Rambow, 2007).

The greater the linguistic distance between the source language and the target language, the greater are the challenges encountered by NLP applications, particularly MT systems. The Arabic language belongs to the Semitic family, which is distinct from the Indo-European languages, including English. For example, Mohammad et al. (2016) argue that languages such as Spanish, German, and French are much closer to English than Arabic is to English, especially in dialectal texts. More importantly, studies in MT assessment generally focus on Arabic-to-English translation, which has been the central area of interest. In contrast, the translation from English to Arabic assessment has received less attention (Ameur et al., 2020).

Although some linguistic challenges, such as word ambiguity, can be observed in various languages, Arabic MT systems still encounter unique linguistic challenges beyond the surface-level interpretation of words. Among the most recognized obstacles for MT systems in the Arabic language is morphological complexity. Due to Arabic’s rich morphology, where derivational and inflectional variations are embedded within single words, modeling English-Arabic MT systems becomes challenging in pre-processing tasks such as tokenization and alignment (for further details, see Khemakhem et al., 2013). Ameur et al. (2020) offer an additional overview of the challenges that affect the accuracy of Arabic MT systems. For example, the study demonstrates that free word ordering in Arabic sentences and word composition make it difficult to accurately map the syntactic structure to English. Furthermore, the out-of-vocabulary terms issue, which refers to the phenomenon of encountering words during the MT process that do not appear in the system's vocabulary, remains a challenge, particularly in specialized or low-resource contexts (e.g., domain-specific terminology).

Despite these linguistic challenges, several MT assessment studies have shown that commercial MT systems, such as Google Translate and Microsoft Bing Translate, can produce comparatively accurate results. Almahasees (2018) conducted a translation quality assessment of the accuracy of Google Translate and Microsoft Bing Translate using linguistic error analysis and error classification. The evaluation results indicated that both online MT systems performed exceptionally well in orthography[10] and grammar (more than 90%), whilst also achieving good results in lexical and grammatical collocations (more than 70%). Similarly, Hadla et al. (2014) evaluated online Arabic-English MT, namely Google Translate and Babylon Translate, using the BLEU method. Their findings indicate that Google Translate outperforms Babylon Translate overall in terms of accuracy for English and Arabic translations. Almahasees (2021) evaluated the performance of three MT systems (Google Translate, Microsoft Bing Translate, and Sakhr) across different linguistic aspects. The author reported that Google Translate outperformed the other systems and achieved the highest scores in terms of accuracy when translating texts from global organizations such as the WHO, UN, and UNESCO. Rapid advances in MT technologies have significantly contributed to the notable improvements observed in commercial MT applications as developers continuously enhance and refine these systems.

More recent Arabic MT assessment studies further examined the accuracy of MT systems' performance against the newly emerged LLMs, which have demonstrated superiority in various NLP applications in recent years. It has been argued that, despite being designed for general-purpose use, LLMs can serve as translation tools due to their large-scale language model capabilities and their ability to generate coherent, context-aware text. As a result, researchers have started to evaluate their effectiveness in translation compared to MT systems that are specifically designed and trained primarily for translation tasks. For example, Banimelhem and Amayreh (2023) compared ChatGPT (GPT-3.5 architecture) to 15 popular commercial MT systems, including Google Translate, Alibaba Translate, modernMT, Argos Translate, and Reverso, all of which use advanced NMT and utilize large-scale data. The authors employed three evaluation metrics to assess the quality of English-to-Arabic

[10] Orthography is the study of a language's spelling.

translation. Their findings indicated that commercial MT systems, such as modernMT, Reverso, and Google Translate, outperformed ChatGPT by a notable margin.

Similarly, Habib et al. (2025) conducted a quality assessment study comparing the new ChatGPT-4 engine with six well-known NMT systems, including Google Translate, Microsoft Bing, and Amazon Translate. In their evaluation using the BLEU metric, the authors reported that ChatGPT-4 outperformed the alternative MT systems, achieving a score of 59.11. Nevertheless, the performance gap was relatively small compared to certain MT systems, specifically Google Translate, which followed ChatGPT closely at 56.76. These studies, among others, have demonstrated that MT quality has improved significantly. Therefore, it can be argued that MT systems can serve as a feasible bridge in downstream Arabic NLP applications such as cross-language sentiment analysis.

Although Arabic MT assessment studies have significantly contributed to evaluating the rapid advances in MT technologies, a notable gap remains in the research regarding Arabic MT systems within the context of finance and business narratives. Assessing MT systems within the finance or business realms offers essential insight into their ability to manage specialized language, such as that used in financial discussions. This is particularly critical because the Arabic language contains financial and business terminologies that lack equivalents in the English language. For example, Islamic finance applications are commonly available in Arabic-speaking countries through financial institutions and corporations. However, most studies that investigate the Arabic-English textual context with respect to economics and business communications are limited to human linguistic translation challenges, such as metaphoric expressions, economic terminologies, cohesion and omission errors, and lexical aspects (e.g., Al Obaidani, 2018; Harahap et al., 2019; Talafha et al., 2024). Assessing the financial Arabic-to-English or English-to-Arabic narratives from the standpoint of MT systems is extremely rare and primarily confined to semantic and adequacy accuracy.

2.6.2 Machine Translation Evaluation Through Sentiment Analysis

As the CLSA literature has expanded and attracted the attention of researchers, a distinct body of research has emerged focusing specifically on the impact of MT on sentiment classification performance. This represents a more focused effort to understand the reliability of sentiment preservation across different languages. The use of MT in textual sentiment analysis poses a challenge due to the potential loss of meaning and polarity during translations. As previously discussed, textual sentiment is domain-sensitive, and words may convey different meanings in financial settings. Furthermore, MT presents further challenges in Arabic due to the linguistic dissimilarities between Arabic and English.

A few Arabic studies have proposed various experimental settings to evaluate the preservation of sentiment translation when mapping sentiment resources between Arabic and English. For example, Mohammad et al. (2016) conducted a comprehensive study to assess the feasibility of using MT in sentiment analysis across Arabic and English texts on social media. Their approach involved analyzing the effect of Arabic-to-English and English-to-Arabic translations on sentiment by utilizing the corpora and lexicons in both languages. They conducted their assessment based on manual and automatic translation using Google Translate and a phrase-based MT system[11]. In their experiment, Arabic text was translated into English (both manually and automatically) and then the English text was annotated for sentiment labeling (also performed manually and automatically). The second step involved comparing the sentiment labels assigned to the translated English and manual annotations of the Arabic text. If the sentiment annotations were similar, the impact on translation was minimal. The same approach was applied to measure the sentiment impact on English text and lexicon translated into Arabic but with automatic translation exclusively. Ultimately, they conducted the sentiment analysis task using the NRC-Canada Sentiment Analysis System[12], a machine learning algorithm. The results indicated that manually labeled text, which has been translated from Arabic to English, achieves a 71.31% match, even though sentiment labeling for both languages is also conducted manually. The authors argue that the impact of English translation on sentiment is not significant because 71.31% is close to the agreement among human sentiment annotations of the original Arabic text, which is 73.82%.

Furthermore, the English sentiment system exhibits a competitive match of 67.73% when applied to the automatically translated text from Arabic to English. Interestingly, the comparison between the Arabic manually labeled sentiment text and translations of the manually and automatically labeled text achieved a competitive result of 62.08%, which exceeded the match rate of manually translated sentiment-labeled text (57.21%). Their assessment focused on the quality of sentiment annotation translation between Arabic and English.

Similarly, another experimental study was conducted by Barhoumi et al. (2018) to evaluate MT systems in terms of sentiment classification in the Arabic language using LABR,

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[11] In their experiment, the translation from Arabic to English was done using in-house translation system, Portage, multi-stack phrase-based MT (Cherry & Foster, 2012). For English to Arabic translation, they used Google Translate https://translate.google.com

[12] The System utilizes a supervised statistical machine learning approach for text classification, which incorporates surface-form, semantic, and sentiment features. For more details, see work done by Kiritchenko et al. (2014).

a corpus consisting of book reviews written in MSA. The study's evaluation process involved three steps. First, the authors established the baseline Arabic sentiment system by training machine learning classifiers, logistic regression, and a multi-layer perceptron model. The second step involved translating the Arabic texts into English to obtain the equivalent English version. The translation was obtained using the LIUM[13] system, which is based on the statistical MT engine Moses[14] (Koehn et al., 2007). Moses' engine accepts large quantities of parallel corpora and uses co-occurrence analysis of phrases and words to infer translation correspondence between the source and target languages. Lastly, the authors applied a sentiment classifier to the translated documents. The performance of sentiment classification was measured using the error rate metric, which determines the percentage of incorrectly classified examples. The authors reported that the Arabic baseline system recorded an error rate of 25.37%, whereas the Arabic-translated documents recorded an error rate of 23.70%. The reduction in the error rate was justified by a pre-processing step on the dataset, removing all non-translated words such as dialectal words, misspelled words, and proper names. Overall, the authors confirmed that sentiment analysis of Arabic text translated into English yields competitive performance compared to monolingual sentiment analysis using the original Arabic text.

The findings of both Arabic MT experiments conducted by Mohammad et al. (2016) and Barhoumi et al. (2018) indicate that sentiment can be preserved to a considerable extent, suggesting that MT systems may offer a feasible means of bridging the resource gap between Arabic and English for sentiment analysis tasks. However, these studies employed datasets that are considerably different from the type of text used in formal financial disclosures. Social media microblogging, whilst presenting unique challenges to MT systems such as high lexical and dialectal variation as well as being highly unstructured, differs from the language used in Arabic financial discourses, which are crafted in highly structured MSA. Additionally, MT systems are susceptible to the domain of the text. Financial texts contain specialized terminology that is unique and rarely found in general-language texts, which may affect sentiment classifiers and translation models when processing financial narratives in the Arabic-English pair. The performance of sentiment classification models through MT application when applied to specialized text, such as financial discourse, remains an open question.

[13] https://lium.univ-lemans.fr/

[14] http://www2.statmt.org/moses/

Other studies have employed similar experimental designs across various languages to evaluate the MT system for sentiment analysis applications. For example, Balahur and Turchi (2014) assessed the effectiveness of Google Translate, Bing Translate, and Moses engines in detecting sentiment after translation in three languages, namely French, German, and Spanish. Their primary objective was to evaluate the efficiency of using automatic text translation in training a sentiment analysis classifier. Similarly, Bilianos and Mikros (2023) used the Google Cloud Translation server to evaluate the efficacy of MT in CLSA settings, including translating Greek and Italian texts into English and vice versa. Their experiment shows that when translating English text, specifically product reviews, into Greek and Italian, classifiers trained on the translated data achieved a level of performance that is close to that of the original English dataset. The authors further conducted a round-trip experiment through an intermediate language (e.g., English to Greek to Italian) and the accuracy of the classification decreased by a small margin, remaining comparable with the original textual data. Several studies have indicated the reliability of MT for leveraging rich-resource languages and demonstrated competitive performance in sentiment analysis applications (e.g., Chinese: Wan, 2008, 2009; German: Lohar et al., 2017; Bengali: Sazzed & Jayarathna, 2019).

Although prior studies have proposed various experimental methods to measure sentiment impact after translation, the motivation behind these studies is the feasibility of utilizing state-of-the-art sentiment systems developed for English, a dense resource language, to analyze textual data from low-resource languages. Furthermore, the evaluation of data annotation or labeling quality (e.g., positive, negative, neutral) is the central focus of previous studies. Data annotation is essential to train a machine learning classifier and, therefore, assessing its quality is crucial to ensuring good performance.

To that end, most MT assessments conducted in sentiment analysis settings are intended for general purposes and business-oriented narratives in Arabic and other languages tend to receive less attention, despite a large body of literature investigating MT applications in sentiment analysis. An exception is the work of Zhang et al. (2017) which examined whether sentiment is preserved when financial texts are translated from English into German using human translators and MT systems, including Microsoft Translator, Google Translate, and Google Neural Network (NMT). They constructed a gold-standard English corpus annotated by a financial expert, which was then translated into German using different translation approaches. In their evaluation experiment, the authors employed two approaches, including the BLEU method and financial experts, to assess the machine output. Their findings revealed that MT systems, specifically Google Translate and the Google NMT model, achieved sentiment preservation levels comparable to those of human translators, suggesting the reliability of MT systems in handling specialized financial text. To the best of the researcher's knowledge, no prior study has evaluated Arabic-English MT in financial narratives from a sentiment analysis perspective.

2.7 Concluding Remarks

In summary, the literature review addresses significant gaps identified in the existing literature concerning financial textual sentiment analysis, particularly within the context of the Arabic language. First, the Arabic language lacks the resources to capture the tone in financial narrative settings. The finance literature has highlighted the superiority of domain-specific resources, such as sentiment dictionaries, in gauging the tone in English financial texts. Second, despite the growing interest in sentiment analysis, no prior study has examined the existing Arabic sentiment dictionaries within financial contexts or conducted a comparison with finance-oriented lexicons. The Arabic language exhibits considerable structural and morphological complexity, and word polysemy is significantly influenced by domain-specific usage, requiring closer attention to sentiment interpretation in financial narrative contexts. Third, while MT has advanced considerably, thereby enabling CLSA, no previous research has systematically examined sentiment preservation in Arabic-English financial documents or evaluated the reliability of such translations for downstream sentiment analysis tasks. Finally, the role of textual sentiment in financial markets has been relatively underexplored, particularly within the context of the Arabic language, with only a few attempts having been made to address market-related phenomena from the textual analysis perspective.

With these gaps in mind, the current research develops an Arabic financial sentiment dictionary to address the lack of a finance-oriented Arabic dictionary for sentiment analysis. Second, the research validates the dictionary's effectiveness by comparing it with a general-purpose Arabic sentiment dictionary. Third, the study evaluates sentiment preservation across Arabic-English financial text translations, examining whether the machine-translated text retains the original polarity and serves as a bridge in downstream sentiment analysis applications. Finally, the research employs the proposed Arabic financial sentiment dictionary to empirically test whether financial markets respond differently to bilingual tone in the SSE market.

Chapter 3. Research Methodology

3.1 Introduction

As reviewed in Chapter 2, the Arabic language is regarded as a low-resource language in the NLP literature. Additionally, the Arabic financial sentiment analysis literature lacks proper resources for measuring tone in financial narratives. This chapter aims to develop a finance-oriented Arabic dictionary that considers the domain attribute of word polysemy. The NLP advancements gap between Arabic and English reveals significant differences between the two languages. Hence, most Arabic sentiment resources were initially designed to treat English-language content and later mapped to the Arabic language. Mapping the English resources into Arabic is achieved using various techniques. By relying on the English Loughran and McDonald's (2011) dictionary (LM dictionary), this chapter introduces the ArFinSD, documenting its construction approach.

Furthermore, minimal efforts have been dedicated to measuring textual financial sentiment in Arabic. Despite the regulation of accounting standards, corporate financial narratives may convey considerable forward-looking information that is not explained by financial performance. Hence, the company's management entirely influences the narrative components of public disclosure, including annual reports, quarterly reports, earnings press releases, and the management discussion and analysis (MD&A) subsections. While two companies may have identical financial accounting numbers, the messages conveyed in their press releases regarding their current performance and future expectations can vary significantly (Henry & Leone, 2016). Finance-oriented dictionaries have shown a robust ability to gauge sentiment in financial settings more accurately than general dictionaries, as illustrated in the preceding chapter.

The research will employ a dictionary-based approach to measure financial sentiment across Arabic financial corporate disclosures and their corresponding English versions. To conduct sentiment analysis, the research will rely on the LM dictionary and the ArFinSD to assess the tone in financial corporate discourses. To achieve this, the research establishes an ArFinSD by utilizing the LM English dictionary. Due to the significant dissimilarity between Arabic and English, additional steps and linguistic techniques are employed to develop the ArFinSD and measure tonal words. To test the capabilities of the developed Arabic dictionary, the research will conduct a comparative sentiment analysis between Arabic financial corporate disclosures and their corresponding English versions. Consequently, the study aims to investigate whether finance-oriented dictionaries outperform general-purpose dictionaries in Arabic financial settings. To evaluate the effectiveness of the Arabic financial dictionary in measuring sentiment in financial settings, a comparative analysis will be conducted against a general Arabic dictionary.

Following the construction of an Arabic financial dictionary, the research will investigate the impact of MT on textual financial sentiment in Arabic and English. One approach in the CLSA literature used to measure textual sentiment is to rely on MT to translate the textual data from a low-resource language to a high-resource language, such as English. This methodology has enabled researchers to leverage more advanced sentiment models and lexicons designed explicitly for the English language. However, such a methodology may present various logistical challenges and loss of sentiment, particularly in the Arabic language. The research aims to investigate the impact of MT systems on the sentiment of Arabic-English financial disclosures.

This chapter is structured as follows. Section 3.2 presents the construction process for the ArFinSD, documenting its mapping approach. Section 3.3 provides the conceptual frameworks for sentiment analysis carried out in three distinct settings. Section 3.4 outlines the negation handling framework for Arabic and English sentiment analysis. Section 3.5 presents the sentiment measurement adopted in this research. Section 3.6 provides the agreement validation methodology across the proposed sentiment analysis frameworks. Lastly, the chapter concludes with Section 3.7, a discussion of the limitations and constraints concerning the research design and methodology.

3.2 The Creation of the Arabic Financial Sentiment Dictionary

3.2.1 Introduction to Lexicon Construction Approaches

The process of mapping English sentiment lexicons to other languages differs and is heavily determined by the focused language's characteristics and NLP resources. Several methods have been proposed to adapt English lexicons for use in Arabic sentiment analysis. The motivation behind mapping sentiment lexicons to Arabic determines the adaptation methods and process. The common motivation is to map English sentiment dictionaries into Arabic to extract features by identifying sentiment words and expressions. More importantly, the main objective of building such a lexicon is not to create a domain-oriented sentiment dictionary but rather to overcome the scarcity of sentiment lexicons in general Arabic sentiment application. This is useful because each word in the original lexicon is assigned a polarity which can be used to extract features in sentiment analysis. Studies incorporate these polarized words to overcome the problem of subjectivity and sentiment analysis (SSA) in identifying sentiment-bearing words. However, whether words carry the same connotation across bilingual adaptations is not prioritized.

To that end, in the Arabic language, several studies have utilized AWN to construct sentiment lexicons by mapping and linking the AWN entries into SentiWordNet, an English sentiment lexicon (Alhazmi et al., 2013; Badaro et al., 2014; Eskander & Rambow, 2015). Another approach to constructing Arabic sentiment lexicons is to borrow and translate English sentiment seed words from an English lexicon into Arabic and then expand these words by including synonyms and antonyms. For example, Abdulla et al. (2014a) and Abdulla et al. (2014b) used a manual approach to create an Arabic lexicon by borrowing 300 seed words from SentiStrength, an English sentiment dictionary. The authors then translated the seed words into Arabic using an English-Arabic dictionary. They subsequently expanded the seed words by adding synonyms and assigning them to the same sentiment classification as the original word.

Furthermore, researchers also utilize well-established English lexicons by relying entirely on automatic translation, such as Google Translate or Microsoft Translate, to map English lexicons to Arabic. This step is followed by manually revising the translated words to correct inaccurate translations and remove those that are unfit for use. For example, Awwad and Alpkocak (2016) utilized translated versions of the MPQA and Harvard IV-4 inquirer dictionary to perform dictionary-based sentiment analysis. Similarly, Mohammad et al. (2016) utilized Google Translate to translate several English lexicons, including the Bing Liu Lexicon and MPQA, among others, into Arabic to overcome the scarcity of Arabic NLP resources, arguing that MT can bridge the gap. Due to MT's substantial advances, mapping English lexicons into Arabic is feasible, although it requires manual revision. Nonetheless, their application of the sentiment analysis is not domain-specific. Whether the translated sentiment word carries the intended meaning of the source word is not evaluated.

Mapping a domain-oriented sentiment dictionary to another language requires a more sophisticated method for representing the target domain in the target language. In the Arabic NLP literature, there have been rare attempts to map English domain-oriented sentiment dictionaries into Arabic. One exception is reported in Sikos et al. (2014) in which the authors attempted to map the LIWC to Arabic, although it is not a one-to-one mapping. The authors first aimed to enhance the English version of LIWC by expanding it prior to its translation into Arabic. The LIWC stemmed entries were initially mapped to the English WN lexical database, increasing its entries from 915 to 3,981. The dictionary was further expanded using the PageRank algorithm to identify additional synonymous words that are semantically related, resulting in 6,495 total words identified. Lastly, these words were automatically translated and then manually filtered, yielding a total of 15,335 in the final Arabic LIWC resource.

3.2.2 Mapping the LM Dictionary into Arabic

Initially, the research implements and translates the latest version of the LM word lists[15] (specifically the positive, negative, and uncertainty word lists) into Arabic to create an Arabic financial sentiment dictionary. Loughran and McDonald (2011) update the LM dictionary annually, arguing that language is dynamic, new terms enter the business vocabulary, and financial narratives change over time. Furthermore, the original LM dictionary contains inflectional forms rather than normalized forms. The authors employed word inflections (e.g., achieve, achieving, achieved, achievement, achievements, achieving, achieves) and argued that these forms are more accurate in representing the intended sentiment word than other normalization techniques, such as stemming. The authors of the LM dictionary relied on word frequency to construct the word lists, with a threshold of occurrences required for inclusion in one of the seven lists[16].

According to the LM dictionary's documentation[17], the inclusion of words in the Master Dictionary, which serves as a foundation for identifying the sentiment lists, is based on a

[15] The last version was updated in February 2024.
[16] The word lists and Master dictionary which includes more additional data are available at https://sraf.nd.edu/.
[17] https://sraf.nd.edu/loughranmcdonald-master-dictionary/

frequency threshold applied to 10-K reports. If an inflected form meets the threshold and is found in the 2of12inf dictionary database, it is included in the dictionary. Meanwhile, if a word does not appear in the 2of12inf but reaches frequencies of 50 occurrences or more, it is classified as part of the 'orphan tokens collection.' These words are then manually reviewed for possible inclusion in the Master Dictionary and may subsequently be assigned to one of the sentiment lists. Table 3.1 presents the number of sentiment words in each category of the LM dictionary. The word lists contain 2,345 negative words, 347 positive words, and 297 uncertainty words. It is worthy of note that 40 words of the uncertainty list overlap with the negative list. In addition, the positive and uncertainty wordlists are substantially smaller than the negative word list. The authors emphasize that it is difficult to find positive words that are less likely to be compromised (Loughran & McDonald, 2011). For example, managers might use the words 'improving' or 'enhancing' instead of 'improved' or 'enhanced,' which suggests a continuous process rather than a finished one.

During the translation of the LM dictionary, I primarily focus on the positive, negative, and uncertainty wordlists for several reasons. First, the primary objective of this thesis is to bridge the gap in Arabic sentiment analysis by creating an Arabic finance-oriented sentiment dictionary. To accomplish this, I prioritized the most extensively tested LM wordlists in English and other languages, specifically those that gauge financial tone in narrative settings. To illustrate, the negative tone, for example, has been superior in the finance and accounting fields in measuring sentiment regarding financial market reactions and behavior. This is unsurprising because early studies relied heavily on general negative word lists such as the Harvard General Inquirer word list (Tetlock, 2007; Engelberg, 2008; Tetlock et al., 2008) and the Diction optimism list (Li, 2010; Davis et al., 2012; Demers & Vega, 2014). However, these lists have been shown to be misleading by a considerable margin compared to the LM dictionary.

Second, the choice of any list from the LM dictionary is primarily determined by the study's scope of interest. Each word list in the LM dictionary has been applied to address different topics throughout the finance literature. This is important because not all words within the LM dictionary are unique and several terms overlap with other categories. For example, many words in the negative list overlap with categories such as Strong Modal, Weak Modal, Constraining, and Complexity. Another example of word overlapping can be observed in the Weak Modal list which overlaps entirely with the Uncertainty list. One exception is the Litigious list which comprises 927 unique words out of the five categories (79.5% of the 1,128 total words). As a result, researchers have employed unique categories of the LM dictionary to test different hypotheses and answer research questions.

3.2.3 Bilingual Mapping Translation Process

The research relies on manual, word-by-word translation to map each word in the LM dictionary to Arabic. In the translation process, I initially start by translating each entry in the LM dictionary, considering all its possible parts of speech (POS). This is critical because conducting the manual translation process before determining the word’s POS leads to translation ambiguity, particularly in words where not all inflection forms are included. For instance, according to LM wordlists, the word ‘dream’ takes only one form, yet it can be interpreted as a noun or a verb. The research relies on the Penn Treebank POS tagsets to manually assign each word in the LM dictionary to its corresponding part-of-speech tag. The POS tagsets are a list of grammatical categories used in various NLP and computational linguistics projects. As a result, the word ‘achieved’ is tagged once as a past verb (VBD) and once as an adjective (JJ). The POS tagging provides a clear interpretation of words during translation.

Next, the researcher creates a parallel preliminary Arabic version of the LM dictionary utilizing Arabic-English dictionaries and thesauruses. At this stage, each English word is translated into potential Arabic counterpart candidate/s. Several English words are translated as two- or three-word expressions, thereby introducing a multidimensional list of Arabic words. The original LM wordlists are consistent with a one-dimensional list of words. Several English words take two or three dimensions when translated into Arabic. For example, the word *proficiently* translates to بطريقة بارعة & بشكل متقن. Multi-dimensional words primarily stem from the translation of English adverbs and negative words with embedded negation cues (e.g., misprice, mismatching, irreparably, incomplete, efficiently, and favorably). The research adapts n-gram (unigram, bigram, trigram) dimensionality up to three-word phrases. These words are categorized by dimensionality, yielding three lists within each category. Translation candidates of more than three dimensions were disregarded.

Furthermore, additional processes are applied to the preliminary parallel Arabic version. For example, several English words lack direct Arabic equivalents in translation. To address this issue, words without direct equivalents are translated into their closest Arabic equivalents, where applicable. Next, each Arabic translation candidate is evaluated based on sentiment orientation. Sentiment words that do not reflect the intended sentiment orientation were excluded. Additionally, words that could be interpreted as positive or negative, or as positive or uncertain, were excluded. More importantly, the translation candidates are evaluated based on their use in financial contexts that align with English-language usage. After all checks are conducted, the research establishes an original version of the sentiment dictionary. This version is further implemented to establish the final version of the Arabic financial sentiment dictionary.

3.2.4 Inflections and Lexical Morphology

Sentiment analysis is a significant challenge in the Arabic language due to its morphological richness. The Arabic language includes various grammatical and morphological features including number, gender, grammatical aspect, syntactic case, mood, definiteness, person, voice, and tense (Abdul-Mageed et al., 2014). Furthermore, the ability to capture a word's morphological categories or inflections depends on the morphological models available in the targeted language. For instance, Bannier et al. (2019) constructed a German version of the LM dictionary relying on an inflection system capable of programmatically generating inflected forms based on predefined POS sets (verbs, nouns, and adjectives). The authors employed such a tool to inflect verbs, nouns, and adjectives to construct their German financial sentiment dictionary. In Arabic, Taji et al. (2018), Smrž (2007), Habash et al. (2009), and Beesley (1996) have introduced several morphological analyzers and generators. Although these models are beneficial for various Arabic NLP applications, constructing a dictionary of inflectional forms remains unfeasible. This is due to the algorithm's linguistic rules for generating word forms which can be affected by both templatic (root/pattern) and concatenative (stems/affixes/clitics) elements.

Several attempts have been made to improve the accuracy of Arabic text classification and address its rich morphological patterns. Two normalization techniques that have been extensively employed in the ASA literature to address linguistic complexity are stemming and lemmatization. The stemming task involves dealing with suffixes, prefixes, and infixes, meaning that the stem can be located within the root (Duwairi and El-orfali, 2014). According to a comparative study on Arabic stemming tools conducted by Dahab et al. (2015), more than twenty stemmers have been developed to enhance Arabic NLP applications. However, stemmers are known for over- or under-stemming by blindly chopping words (Al-Shammari and Lin, 2008). The next chapter provides further details on the stemming approach as a word representation. Although stemming is a practical approach across a variety of NLP tasks, in dictionary-based analysis, it introduces sub-lexical ambiguity at the word level. Arabic words are constructed upon root-based patterns in which distinct words can share the same base.

When stemming is applied, a substantial number of words, although they are not morphologically related, are grouped under a stem root.

Alternatively, more advanced normalization techniques have been introduced to overcome the morphological complexity in Arabic. Lemmatization is a normalization technique that considers the structure of the word. A lemma is the look-up form in the dictionary that contains the transformation of all inflected word forms (Korenius et al., 2004; Mubarak, 2018). A lemma-based approach, as a foundational unit in a sentiment dictionary, is widely used to construct Arabic lexicons. ArSenL (Badaro et al., 2014) and SLSA (Eskander & Rambow, 2015) are two state-of-the-art general dictionaries that are constructed on a lemma-based approach. The lemma-based approach accounts for all morphologically inflected forms being grouped under the same POS category. In other words, lemmatization reduces a word to its look-up form while preserving its POS, thereby accounting for the complex morphology of the Arabic language. More importantly, identifying the correct lemma form of a given word requires a robust morphological analyzer to perform the disambiguation. Further details on the lemmatization technique are discussed in the following chapter.

In constructing the Arabic financial sentiment dictionary, the word's lemma is considered as an input. At this stage, the preliminary Arabic dictionary was converted into a lemma-based dictionary using the CAMeL tool (Obeid et al., 2020), an Arabic NLP library. The research employs morphological analyzer models in CAMeL to identify and transform the entries into lemmatized forms. Therefore, an additional version of the Arabic sentiment dictionary is created by matching each original Arabic translation to its lemma form, POS, and English gloss. Each lemmatized entry was manually checked against the original Arabic translation candidate/s and mapped back to the English LM dictionary. The finalized ArFinSD consists of 2,121 negative words, 565 positive words, and 418 uncertainty words. Table 3.1 presents the number of sentiment words and their categorical proportion across the established Arabic sentiment dictionary in comparison to the LM dictionary. The negative category includes 1,105 one-dimensional, 756 two-dimensional, and 260 three-dimensional words. The positive category contains 355 one-dimensional, 197 two-dimensional, and 13 three-dimensional words. The uncertainty category includes 182 one-dimensional, 170 two-dimensional, and 66 three-dimensional words. The complete word lists for the sentiment categories, organized by the translation process phase, dimensionality, and their English translation, are presented in Appendix A.

Table 3.1 Number of Sentiment Words in Dictionaries

	LM dictionary	ArFinSD
Negative List	2345	2121
Positive List	347	565
Uncertainty List	297	418
Total	2989	3104
In (%)		
Negative List	78.4%	68.3%
positive List	11.6%	18.2%
Uncertainty List	9.9%	13.5%

The table illustrates the number of words that appeared in the LM dictionary and the ArFinSD. Appendix A provides the ArFinSD based on the categorical class and English translation corresponding equivalents from the LM dictionary.

3.3 Sentiment Analysis Frameworks

The research will employ a dictionary-based sentiment approach to capture tone using various sentiment dictionaries and financial corpora across Arabic and English, thereby addressing the research questions. The dictionary-based sentiment analysis approach has been widely used in the finance and accounting literature to test various market-related hypotheses using financial texts (Loughran & McDonald, 2011; Henry, 2008; Henry & Leone, 2016; Guo et al., 2022). On one hand, English finance-oriented dictionaries have demonstrated their ability to capture tone in financial settings more accurately than general-purpose dictionaries. On the other hand, the Arabic language is morphologically far more complex and polysemous. There is a significant lack of proper and specialized resources for financial sentiment analysis in Arabic that can capture the tone in financial settings. The ArFinSD, developed in this research, addresses this gap by providing a finance-oriented dictionary to gauge sentiment in Arabic financial applications.

The research employs a multi-stage sentiment analysis design to address the research questions and meet the stated objectives. After establishing the ArFinSD, three sentiment analyses are carried out to capture the tone in Arabic-English financial narratives. Multi-stage sentiment sequential analyses are conducted, each addressing a distinct research objective related to the Arabic financial textual sentiment. The first sentiment analysis establishes a baseline by assessing the cross-linguistic consistency of sentiment analysis, comparing the original Arabic financial disclosures with their English counterparts using the ArFinSD and LM dictionary, respectively. The second sentiment analysis evaluates the performance of the ArFinSD in comparison to a broader, general-purpose Arabic lexicon. The third sentiment analysis examines the impact of translation on original financial disclosures and the extent to which textual sentiment is preserved. The following subsections present each analysis, highlighting its motivation, objective, and design. The following chapter outlines the corpus construction, NLP pre-processing, and methodological implementation employed in the three sentiment analyses.

3.3.1 Baseline Sentiment Analysis of Financial Text: Arabic and English

To address the research questions, the study employs a dictionary-based approach, using the newly developed ArFinSD and the LM dictionary to analyze Arabic financial disclosures and their English counterparts (data description is presented in Chapter 4). The cross-language sentiment analysis provides a baseline for evaluating how well the proposed ArFinSD captures financial tone relative to the LM dictionary. The analysis establishes a benchmark for sentiment analysis measures across the two languages. More importantly, the sentiment comparison analysis determines whether the two sentiment dictionaries, each constructed within its respective linguistic context, capture comparable tone across the two versions of financial disclosures.

To that end, although the ArFinSD was developed based on the LM dictionary through word-by-word manual translation, the two lexicons are not direct equivalents to each other. The ArFinSD, as documented in Section 3.2.4, is based on a lemma as a word representation within the predefined sentiment categories. The LM dictionary, on the other hand, relies on inflected forms that are selected based on the frequency threshold set by the authors. As a result, the lemma form would theoretically cluster all morphological variants that reflect the exact grammatical class of the word. Furthermore, the ArFinSD includes n-gram words up to three dimensions as predefined sentiment multi-expression words. In contrast, the LM dictionary consists of only one-dimensional words across all sentiment categories. These differences in construction strategies, such as morphological adaptation and multi-dimensional word inclusion, contribute to variations in lexical coverage. Several implementation factors, such as negation detection and pre-processing procedures, may also influence sentiment classification across the two dictionaries and these are discussed further in Chapter 4.

Despite dictionary differences, the analysis remains critical at this initial stage because it reveals whether the expression of financial tone is consistent across the Arabic documents and their counterparts or whether it depends on other aspects and features specific to each language. The cross-language analysis serves not only as a baseline for further study but also uncovers the degree of association between the sentiment classification across the two versions of the texts. A high correlation in sentiment expression across two versions of a document indicates that both dictionaries are capable of capturing the tone, despite linguistic variations. Further details concerning the data used and methodological implementations for the cross-language comparative analysis are presented in Chapter 4.

3.3.2 General Dictionaries and Finance-Oriented Dictionaries

To address the research question (*To what extent does the proposed Arabic financial sentiment dictionary yield accurate results in measuring sentiment compared to Arabic general dictionaries?*), the research conducts a sentiment analysis comparison between the ArFinSD and an Arabic general dictionary. A key concern when applying a general dictionary to domain-specific text is the risk of sentiment misclassification. Words frequently found in financial contexts may be misclassified by general dictionaries, resulting in incorrect sentiment analysis. This misclassification, whether overstating positivity, understating negativity, or failing to recognize domain-specific usage, can significantly hinder the ability to accurately measure tone in financial text settings. A substantial body of research in the English finance and accounting literature has documented that finance-oriented dictionaries are better suited to assessing the sentiment in financial narratives. For example, Loughran and McDonald (2011) demonstrated that the negative sentiment word list from the Harvard dictionary has notable limitations in business narratives, and they suggested that nearly 75% of negative words in the Harvard negative list are misclassified. A later study by the same authors found that approximately 70% of pessimistic diction and 83% of optimistic diction frequencies are incorrectly classified (Loughran & McDonald, 2015). These studies emphasize that general-purpose dictionaries are inappropriate for measuring the tone in English financial settings.

The concern remains relevant in the context of Arabic sentiment analysis. In addition to the Arabic language's morphological complexity and dialectal variations, domain-specific language is one of the most challenging aspects in sentiment analysis. Although several studies have acknowledged the challenges posed by domain-specific language (Mao et al., 2024; Oraby et al., 2013; Oueslati et al., 2020; Wankhade et al., 2022), limited effort has been made to examine language usage and sentiment in Arabic financial settings. This gap is especially significant considering Arabic's rich morphology and complex derivational structure. The complexity further makes the word's meaning and interpretation highly sensitive to the context and domain in which they appear. Words used in formal Arabic financial communication often carry meanings and sentiment implications that differ from those used in everyday language. The study aims to assess whether Arabic general-purpose sentiment dictionaries can effectively capture sentiment in financial narrative settings. Furthermore, the analysis aims to investigate how sentiment is interpreted within Arabic financial narratives according to Arabic finance-oriented and general-purpose dictionaries.

To investigate the impact of polysemy on sentiment classification in financial settings, the research conducts a comparative sentiment analysis between the ArFinSD and the large-scale ArSenL (Badaro et al., 2014). The ArSenL employs a distinctive methodology known as the merge-based approach (Kaity & Balakrishnan, 2020) to construct its lexicon. The dictionary is developed using three primary sources: the AWN, ESWN, and the SAMA morphological analyzer. This process involves mapping Arabic lemmas, identified through the SAMA morphological analyzer and aligned to the AWN, into their equivalent English synsets in ESWN to assign sentiment scores to each lemma. The resulting dictionary is then manually validated regarding the sentiment scores, providing a comprehensive resource. The ArSenL contains 28,780 unique lemmas along with 157,000 synsets. ArSenL is among the most widely utilized dictionaries in the Arabic sentiment analysis literature (El-Halees & Salah, 2018; Assiri et al., 2018; Al Sallab et al., 2015). Furthermore, ArSenL is constructed as a lemma-entry dictionary, and it is primarily based on MSA, which suits the financial text type of corporate disclosure reports because it is classified as formal-style communication. Further details regarding the ArSenL and comparative analysis are presented in Chapter 4.

3.3.3 Machine Translation Impact Assessment

The research aims to address the question (*To what extent does machine translation between Arabic and English affect the sentiment of financial disclosures?*). The study investigates the impact of MT on financial sentiment, determining whether Arabic financial disclosures and their corresponding English versions preserve the sentiment. More specifically, the research aims to determine whether the tone is preserved across languages during automatic text translation. The assessment of MT is conducted through a dictionary-based sentiment analysis framework which is closely related to CLSA studies. The objective of the experiment is to determine whether Arabic-English financial textual sentiment, an area that remains underexplored, is affected by MT. A substantial body of the CLSA literature highlights advances in MT systems that facilitate various sentiment analysis tasks, yet the degree to which sentiment is preserved remains influenced by linguistic differences and the specific attributes of domain-specific texts.

The significance of translation impact assessment stems from the possibility that if MT modifies the sentiment tone in Arabic-English texts, then CLSA studies may yield biased results, especially in domains such as finance where tone has been consistently linked to market reactions throughout the financial literature (e.g., Tetlock, 2007; Loughran & McDonald, 2011; Henry, 2008). This issue is emphasized by the linguistic disparity between Arabic and English pairs which significantly diverges from European language pairs that predominate the majority of the MT and CLSA literature. Arabic is a morphologically rich, highly inflected, and structurally complex language, which influences the mapping process of MT systems into their English equivalents. More importantly, although tone plays a crucial role in the financial market, little attention has been devoted to evaluating sentiment preservation through MT in the context of financial narratives. Hence, the research addresses these gaps by offering critical insight into how MT systems alter financial sentiment in the complex language of Arabic.

The research conducts an MT experiment on Arabic and English financial disclosures using sentiment analysis. This study performs CLSA and applies a two-way experiment design structured around four main pillars:

A. Conduct sentiment analysis on the original financial disclosures (Arabic and English).
B. Automatically translate the original financial disclosures into other languages.
C. Conduct sentiment analysis on the machine-translated financial disclosures.
D. Compare the sentiment preservation between the original version of the financial disclosures and their translated counterparts within the same language framework.

These four pillars are applied in a bidirectional fashion on the Arabic and English original financial documents. The proposed experimental design enables the measurement of whether sentiment preservation holds consistently or varies with the direction of language. The research's experimental design builds upon and expands the work of Mohammad et al. (2016), which explored how translation alters sentiment in Arabic-to-English social media content. In their experimental setup, the authors employ a unidirectional framework to assess the sentiment loss between Arabic and English resulting from MT. In contrast, the current experiment employs a bidirectional framework to assess sentiment preservation across Arabic and English, thereby examining the direction effect of MT on financial textual sentiment.

Typically, in CLSA experimental assessment settings, the sentiment shift or preservation validation is evaluated by comparing sentiment labels of machine-translated text (e.g., sentences or social blog posts) against gold-standard sentiment annotations (Mohammad et al., 2016; Barhoumi et al., 2018). Sentiment preservation is determined by assessing the accuracy of the sentiment classifier against the annotated data. This is crucial in their frameworks because the annotated data marks a fundamental step in the training phase for building sentiment classifiers or utilizing existing advanced models in another language.

In contrast, employing a dictionary-based approach for sentiment analysis has the advantage of eliminating the need for manual data annotation. The dictionary-based approach leverages sentiment dictionaries established specifically to gauge tone in financial settings, without relying on additional data labeling. As a result, the research aims to analyze the preservation of sentiment between the original financial disclosures and their automatically translated counterparts based on sentiment words identified across two versions. The use of a sentiment dictionary and word frequency to measure sentiment loss is what differentiates the research's methodology from previous Arabic CLSA studies. The research will utilize the LM dictionary to measure sentiment similarity across English financial disclosures (original and translated) and the ArFinSD to measure textual sentiment in Arabic disclosures (original and translated).

The study employs an evaluation framework that integrates a dictionary-based sentiment analysis approach with a set of statistical agreement measures. The research's evaluation framework is based on the cross-language adaptation of sentiment dictionary studies outlined in Section 3.6. The set of statistical measures enables a systematic assessment of consistency, absolute agreement, and equivalence in sentiment tone between the original versions and their translated counterparts.

Additionally, the translation is conducted using Google Translate's NMT system, which is accessed through the Google Cloud API. In 2016, Google announced its new MT methodology, moving from traditional Phrase-Based MT to the more advanced NMT system (Wu et al., 2016). This transition enhanced translation quality, making it more feasible to rely on such online MT systems for sentiment analysis. Furthermore, Google Translate is the predominant online MT in CLSA for Arabic and many other languages. Google also offers a paid cloud API that enables the processing and translation of large amounts of textual data. The next chapter illustrates corpus composition along with the MT process, preprocessing steps, and the methodological implementation of sentiment analysis used to assess how well sentiment is preserved following MT.

3.4 Negation in Dictionary-based Methodology

Negation words are a fundamental element of sentiment analysis because they can invert the tone of a given text. Because the BoW approach ignores both the sentence's order sequence and the grammatical structure of the sentence, it is critical to account for negation words. Negation words such as '*not*,' '*none*,' and '*neither'* usually alter and shift the sentiment of the words, changing the sentimental tone from positive to negative and vice versa. There are variant negation categories such as syntactic negation (e.g., no, not, non, never, etc.), morphological negation (e.g., dis-, im-, non-, less, etc.), or diminisher negation (e.g., little, hardly, rarely, etc.) (Farooq et al., 2017). These forms of negation can also be classified as explicit or implicit. The critical difference between the two categories is that, in explicit negation, the negator is a separate cue preceded by a word, whereas, in implicit negation, the negator is embedded within the word's root.

More importantly, handling the negation involves identifying the scope of negation in which the effect of the negation form is determined. The negation scope, also known as the negation window, is typically determined by the static window or punctuation marks (Farooq et al., 2017). The negation window depends on the sentiment analysis methodology, such as sentiment level and algorithm classifiers. Because the dictionary-based method treats the document as a collection of individual words, the static window is well-suited for handling negations. The negation scope of the static window varies and it can be immediately or up to six words preceding the negation words.

Handling negation in finance studies relies on explicit negation with a static window, rather than morphological implicit negations or punctuation marks. The popularity of the simple negation or static negation approach within the dictionary-based method can be attributed to the fact that the BOW technique represents each word or value within the document as a separate numeric occurrence, where the semantic and syntactic relations between words are ignored. Nonetheless, other negation approaches, such as implicit negations, are suitable for sentiment classifiers, including deep-learning-based algorithms that rely on labeled data and consider the text's linguistic and morphological aspects.

The current study considers the English negation words proposed by Loughran and McDonald (2011), where they negate sentiment polarity if a negation form (no, not, non, neither, never, nobody) precedes the sentiment word within a static word window. Several finance studies have incorporated either the negation forms proposed by Loughran and McDonald's research (Huang et al., 2014; Renault, 2017) or a more comprehensive version of these negation words (Brau et al., 2016; Borochin et al., 2018; Correa et al., 2021). All forms of negation used in these studies consist of explicit negation, where the negator is a distinct cue preceding the sentiment word.

Additionally, the negation window within the dictionary-based approach varies, ranging from one word (Huang et al., 2014) to two words (Borochin et al., 2018) and extending up to three words (Loughran & McDonald, 2011; Correa et al., 2021). However, despite using various negation scope windows, no empirical study has examined the performance of different negation scope windows within the finance literature. This gap causes uncertainty regarding which negation scopes yield the best performance in handling negation in sentiment analysis of financial narratives.

The current study adopts the three-word negation scope window for the English language proposed by Loughran and McDonald (2011) and replicated by Correa et al. (2021). The three-word scope window provides a broader context, ensuring that the negator's vicinity captures the sentiment words that are not immediately preceded by the negator. This is crucial because financial disclosures include complex sentences, which can further the distance between negation and sentiment words.

Furthermore, determining whether to apply negation forms exclusively to positive sentiment words or to both positive and negative sentiment words is another crucial element in handling negation in financial narratives. The current research applies negation forms and switches the sentiment for positive and negative words. On the one hand, Loughran and McDonald (2011) only reverse the sentiment of positive words, arguing that in corporate disclosures, management rarely expresses positive news using negated negative words. For instance, it is unlikely to observe the phrase "not terrible earning" in a corporate report to address positive news. In contrast, according to the authors, it is common to address or imply negative news using positive words ("did not benefit").

On the other hand, certain studies have considered switching the sentiment for both positive and negative words. For example, Brau et al. (2016) applied negation to both positive and negative words, arguing that negated negative usage is common in IPO registration documents. Despite the argument that the rarity of negated negative usage is used to address positive news, companies might use negation forms to address positive phenomena. For example, the phrase "not actually reduced" is considered positive after applying the negated negative factor. Furthermore, the decision is also influenced by the research's study design, which considers Arabic language counterparts.

The Arabic language, in contrast to English, is morphologically rich and highly inflectional, resulting in a greater diversity of negation forms. In MSA, the official medium of communication, negation forms differ from those in Dialectal Arabic (DA), which is the informal or spoken language. The challenges associated with handling negation in ASA are widely recognized (Kaddoura et al., 2021; Zahidi, 2020). More importantly, in Arabic, the negator is an explicit cue preceding the word, whereas in English, negation forms can be either explicit or implicit. The morphological complexity of the Arabic language is attributed to only a few attempts at handling negation in ASA. Furthermore, the nature of the Arabic textual data in this research only allows the utilization of negation forms used in formal communication. Corporate documents and disclosures are conveyed in an MSA written style. Nonetheless, handling negation in Arabic has only been studied by NLP scholars and has not been investigated using financial textual content.

Throughout the literature concerning Arabic NLP, five common negation forms are widely used to address the negation aspect in MSA. Duwairi and Alshboul (2015) and Mostafa (2017) employed five negation particles (لا-Laa, ليس-Laysa, لن-Lan, ما-Maa, لم-Lam) in their studies, arguing that these are the most widely used forms in MSA. Similarly, Abdulla et al. (2013) and Abdulla et al. (2014a) utilize six MSA negation forms (لا-Laa, ليس-Laysa, لن-Lan, ما-Maa, لم-Lam, لما-Lma) during their sentiment analysis process. Other studies, however, have used extended versions of the standard MSA negation forms to handle negation in ASA. For example, Touahri and Mazroui (2021) developed a more extensive negation lexicon by leveraging existing Arabic resources and MT to incorporate the available English resources.

Another essential element to consider when handling negation in Arabic is the scope of the negation window. In Arabic, the vicinity of the negation effect has not been thoroughly studied. Predominantly, the negation window is consistent with explicit negation immediately preceded by sentiment words (Abdulla et al., 2013; Abdulla et al., 2014a; Duwairi and Alshboul, 2015; Mostafa, 2017). However, despite the inherent complexity of the Arabic language, corporate communications may use more complex sentences, where a one-word negation window may be unsuitable to capture the whole negation vicinity. By testing a variety of negation scope windows, Assiri et al. (2018) presented evidence that using two- and three-word negation windows yielded more accurate classification performance.

For Arabic negation handling, I consider a similar negation framework applied to the English textual content with minor modifications. First, I utilize the widely used explicit negation forms in MSA (لا-Laa, ليس-Laysa, لن-Lan, لم-Lam) and additional four negation forms (بلا-Bla, دون-Dwn, غير-Gyr, عدم-Edm, عكس-Eks) to express negation. I exclude the negation form (Maa-ما) due to excessive usage of the form in other grammatical contexts. This is because the form (Maa-ما) has various grammatical functionalities and does not necessarily flip the polarity of the sentiment (Kaddoura et al., 2021). The second negation group was utilized as part of the negation lexicon of Touahri and Mazroui (2021). The second group is designed to enhance the likelihood of capturing the reverse sentiment in Arabic because it is more complex than English. Second, the polarity of the positive and negative sentiment words is reversed when the explicit negator precedes them (e.g., Abdulla et al., 2013; Abdulla et al., 2014a; Touahri & Mazroui, 2021). Negating both the positive and negative sentiment words will improve the accuracy of sentiment classification. For example, in the phrase (لم نتعرض الى مخاطر سيوله نقدية خلال العام المالي; we did not encounter liquidity risk during this fiscal year), the polarity of the word (مخاطر) is flipped to positive sentiment. Switching negation on both ends of the sentiment scale is the standard practice when handling negation throughout the ASA literature (Duwairi & Alshboul, 2015; Mostafa, 2017; Kaddoura et al., 2021). Lastly, the research follows the three-word negation scope window rule proposed by Assiri et al. (2018) to determine the vicinity of negation. This is critical not only because of the richness of the Arabic language but also because corporate disclosures, similar to English business content, are carefully crafted and the distance of the negation forms is not immediate.

3.5 Measurement of Sentiment

The dictionary-based approach assumes that individual words are independent, with each word's occurrence represented by a unique vector. This allows the text to be transformed into a word vector count using Python. The research measures the overall sentiment for each document at the document level, as well as the proportion of sentiment categories within each document. I calculate the relationship between positive and negative sentiment words for each document, following the approach of Loughran and McDonald (2015), Davis et al. (2015), and Picault and Renault (2017). The sentiment of each text, *Tone*, is calculated as the difference between the positive and negative words, normalized by the total number of words in each document:

$$Tone = \frac{p - n}{w}$$

Where:

- p represents the number of positive words in the document.

- n represents the number of negative words in the document.
- w represents the total number of words in the document.

3.6 Sentiment Classification Agreement Framework Assessment

Following the establishment of the ArFinSD, the research aims to evaluate its reliability and robustness across various sentiment analysis frameworks and settings. Because the study employs a dictionary-based sentiment analysis approach across the proposed analysis settings in Section 3.3, this section outlines the comprehensive methodological framework used in the analysis. This framework addresses three distinct yet related objectives: (1) assessing the cross-linguistic consistency of the baseline sentiment analysis by comparing the original Arabic financial disclosures with their English counterparts, utilizing ArFinSD and the LM dictionary, respectively; (2) evaluating the effectiveness of ArFinSD within the Arabic financial domain in comparison to a broader, general-purpose Arabic lexicon, specifically ArSenL; and (3) examining the extent to which textual sentiment is preserved after the process of MT between Arabic and English in bidirectional financial disclosure settings. To achieve these objectives, this section details the measurement framework used to assess sentiment agreement and consistency across the three comparative analyses.

Within the NLP literature, researchers have proposed several frameworks to evaluate the agreement between cross-language sentiment classification results. In such evaluations, the study's design and objectives play a critical role in determining the appropriate approach for cross-language sentiment classification evaluation. The primary goal is to assess whether sentiment classification models are able to produce comparative results within a CLSA framework to overcome resource scarcity in the target language, as demonstrated in studies by Al-Shabi et al. (2017), Mohammad et al. (2016), Kajava et al. (2020), and Xu et al. (2022). These models are typically trained using a high-resource language such as English and then evaluated for their capabilities when applied to a lower-resource target language. CLSA studies typically rely on parallel corpora, MT, and multilingual model adaptation to transfer sentiment applications across languages. Evaluation in this field of research usually involves automated or manual translations, validation through annotated corpora, and performance measurements utilizing classification metrics such as accuracy, recall, and F1 score. Therefore, the emphasis is on the model's performance or annotated corpora and the ability to transfer these resources to the target language, rather than directly comparing sentiment results across languages using sentiment dictionaries.

In contrast, other studies have primarily focused on cross-language adaptation of sentiment dictionaries, with the LIWC validation framework serving as a leading example. The LIWC is an English software program that analyzes textual data based on psychological categories, as defined in a dictionary of words. The dictionary has been translated and adapted into several languages, including German, Spanish, Norwegian, Portuguese, Dutch, Serbian, and Italian. During the adaptation into a target language, scholars commonly assess the reliability of the translated version using statistical agreement measures such as correlation or equivalent metrics. For example, during the adaptation of the LIWC into the Dutch language, Boot et al. (2017) applied Pearson and Spearman correlation to assess the equivalence across 564 parallel Dutch and English texts. To ensure the appropriate statistical approach, the authors selected correlation methods based on the skewness of the distributions and considered a coefficient above 0.50 as a threshold for determining linguistic alignment between the English and Dutch versions.

Likewise, Wolf et al. (2008) evaluated the accuracy of their adaptation of the LIWC into the German language, utilizing Spearman correlation to assess the consistency in the rank ordering of the text units across the two LIWC versions. They further applied the intraclass correlation coefficient (ICC), specifically the ICC [3,2] model, based on a two-way mixed-effects design, as described by Shrout and Fleiss (1979). The ICC [3,2] was used to evaluate the agreement between the categories across the two versions of the text. This method of assessing equivalence and reliability has also been applied to adapt LIWC into the Serbian language (Bjekić et al., 2014) and Spanish (Ramírez-Esparza et al., 2007).

In contrast to the LIWC adaptations, which primarily fall within the psychology domain, two studies have focused on adapting and validating sentiment dictionaries for finance-oriented applications within a cross-language framework. Bannier et al. (2019) followed Wolf et al.'s (2008) approach to evaluate the adaptation accuracy of the LM dictionary into the German language. The authors validate their accuracy by computing Pairwise and Spearman correlations between the sentiment categories derived from 1,402 quarterly and annual reports in German and English. In addition, they employed ICC [3,2] to assess the agreement in alignment between the sentiment classification categories in the two versions. They further employ two-sided equivalence testing to confirm that the differences in sentiment categories between the two versions are statistically negligible. Applying a strict validation approach consistent with prior LIWC dictionary adaptations, the authors focus on developing a German finance sentiment dictionary that mirrors the LM dictionary in the German language.

González et al. (2021) applied a less strict validation approach to evaluate their adaptation of the LM dictionary into a joint Spanish and Portuguese equivalent. The authors validated their version of the dictionary by measuring textual sentiment in a sample of financial news retrieved from Bloomberg in English, as well as the corresponding versions in Spanish and Portuguese. The authors only employed a Pearson correlation on the negative, uncertain, and weak modal, as well as the positive word lists. These studies emphasize that the correlation-based statistical validation is a suitable framework for evaluating sentiment dictionary equivalency and reliability, particularly when dictionaries are designed for domain-specific usage and intended to measure sentiment across two languages.

Building upon prior validation approaches, the research aims to assess whether the ArFinSD can produce comparable results to those of the LM dictionary using Arabic financial discourses and their English counterparts. Two statistical measures are applied to assess the cross-linguistic reliability of the sentiment classification: the Pairwise and Spearman correlations. These metrics are used to determine the degree of agreement in sentiment proportions across the sentiment categories, including positive, negative, and uncertainty in both Arabic and English texts. Correlation-based validation is among the most widely employed techniques for evaluating the equivalency and reliability of sentiment dictionaries across languages. These statistical evaluations provide a robust assessment of whether sentiment classifications are preserved across languages despite lexical and structural differences.

Similarly, the research employs correlation-based analysis, utilizing Pairwise and Spearman correlations to assess the degree of agreement between the ArFinSD and the general-purpose Arabic dictionary, ArSenL. Although both dictionaries operate within the same language, utilizing the same word-level presentation (lemmas), they differ substantially in terms of their method of construction, lexical coverage, and polarity classification. The research's objective is to evaluate whether the Arabic general dictionary produces comparable results to the ArFinSD using the dictionary-based approach on financial disclosures.

Lastly, after sentiment analysis is performed and sentiment words and their frequency are obtained and identified across the three categories (positive, negative, and uncertain), the research will evaluate whether the sentiment or *Tone* is preserved between original and machine-translated financial disclosures. The overall sentiment or *Tone* is measured at the document level and provided in Section 3.5. Additionally, the research evaluates the extent of sentiment preservation across individual sentiment categories. The comparison between original documents and their translated counterparts aims to assess whether these ratios remain sufficiently consistent across languages, thereby facilitating the observation of MT preservation in financial Arabic-English CLSA.

Given the absence of gold-standard annotations or human reference translations, the research methodology employs a suite of statistical measures to assess the impact of MT on sentiment analysis based on the results of the dictionary-based approach. These measurements include correlation-based validation using Spearman, Pearson, and ICC [3,2], as described by Shrout and Fleiss (1979). This approach provides a comprehensive assessment of the relationships and consistency between the original financial disclosures and their translated counterparts. Additionally, the research applies the two-sided equivalence test, following the approach of Blair and Cole (2002), to assess the sentiment equivalence between the original annual reports and their translated versions in each language.

Although the current analysis of the impact of translation on sentiment compares sentiment classification results within the same language, specifically between the original and MT versions (e.g., original Arabic vs translated Arabic), at this stage, the evaluation and validation methods established in cross-language studies (e.g., Boot et al., 2017; Wolf et al., 2008) remain directly relevant. This is because the core research's objective is to assess the impact of translation on sentiment classification accuracy and the fundamental sentiment classification relies on a dictionary-based approach. Therefore, the predefined sentiment lexicon under the dictionary-based classification approach serves as a reference benchmark for evaluating whether sentiment is preserved across the original and machine-translated financial documents.

The statistical agreement evaluation framework enables the assessment of the translation's impact across both corpora within the same language, based on sentiment classification accuracy. This accuracy is determined by the words identified in each category, the aggregate sentiment *Tone*, and the categorical proportion of each document across the two versions of the reports. Unlike the current study, traditional MT assessment studies typically evaluate translated text against the 'gold standard' human translation to assess the quality of the translation. Therefore, conventional evaluation measures such as BLEU, error analysis, and F-scores are not applicable to this study. For example, the BLEU algorithm evaluates translation quality in relation to human translation. Zhang et al. (2017) argue that the BLEU algorithm is unsuitable to assess sentiment preservation and should instead be used to evaluate translation quality because it measures quality based on approximating human translation. Similarly, under error analysis, an expert classifies translation errors such as lexical choices, grammatical aspects, and word ordering.

3.7 Methodological limitations

Several methodological limitations must be acknowledged. These limitations primarily stem from the sentiment analysis approach, the challenges of bilingual characteristics between Arabic and English, and the evaluation of sentiment preservation after MT in financial narratives.

Although the sentiment analysis methodology employed in this research has been extensively used in the finance and accounting literature, the dictionary-based approach has several drawbacks. Sentiment analysis is based on the BOW method, which treats the document as a collection of individual words, largely ignoring context. This results in a loss of semantic orientation between words, which can affect the accuracy of textual sentiment classification. Sentiment analysis approaches employing deep-learning algorithms or LLM models have the advantage of learning the semantic and syntactic relations in text, which may lead to more accurate sentiment classification. However, the dictionary-based approach is computationally efficient, easily replicable, and interpretable, which is critical, especially in low-resource languages such as Arabic. The dictionary-based approach is essential due to the research's scope of objectives, ensuring consistent bilingual alignment measures across Arabic and English financial disclosures. Furthermore, the negation detection within the research's sentiment analysis framework mitigates the BoW limitation in capturing semantic and syntactic relations.

Another limitation arises from the ArFinSD construction approach which relies on lemma entries rather than inflected forms. Loughran and McDonald (2011) argue that an inflected form-based dictionary is more accurate in capturing sentiment in financial narratives compared to a normalized form of the words (e.g., lemmatized or stemmed). This has also been confirmed by Bannier et al. (2019) who developed a German version of the LM dictionary to assess the tone in German financial disclosures. However, in the Arabic NLP literature, lemmatized-based word forms are a dominant representation in sentiment dictionaries and this is the most efficient method for addressing the Arabic complex morphological system. The inflectional richness of Arabic words makes an inflection-based dictionary infeasible because identical semantic roots may appear in many morphologically distinct forms. The linguistic normalization of the entries based on lemma form and POS is an essential methodology to ensure consistent and accurate word identification.

Additionally, the research utilizes the Google MT system to evaluate the impact of the extent of sentiment preservation across Arabic and English financial discourses. Specifically, the study utilizes Google Translate's NMT system, which is accessed through the Google Cloud API. Despite recent improvements in the performance of MT systems with the emergence of NMT methods, the quality of translation of the Arabic-English pair remains a subject of ongoing research. Translation techniques and processes depend on the source and target languages (Wang et al., 2022). The greater the linguistic disparity between two languages, the more difficult it becomes for the MT system to produce accurate results.

Furthermore, it is difficult for an online MT system to rely on a single method and each MT provider typically uses numerous techniques to improve translation performance. Although several studies have concluded that MT systems are sufficiently accurate to produce comparative results on sentiment classification tasks for the Arabic-English pair, their performance varies significantly, as demonstrated in Chapter 2. Therefore, the findings may not be fully generalized across MT systems or across future model updates.

To that end, the performance of MT systems may yield different results depending on the direction of translation (English to Arabic or Arabic to English). The Arabic language poses unique linguistic challenges to MT systems due to its morphological complexity and word order flexibility compared to English, which is morphologically and syntactically less complex. Researchers investigating the Arabic-English language pair distinguish between the performance of directional MT, noting that not all directions receive the same level of attention, as highlighted by Ameur et al. (2020).

Another limitation arises from the lack of manually annotated or gold-standard reference translations, which are generally used to evaluate the MT system's performance. However, the research aims to assess the capabilities of MT systems to preserve sentiment across original and machine-translated corporate financial disclosures. Specifically, the assessments are constructed using sentiment words, employing a dictionary-based approach, rather than relying on surface similarity or the overall quality of the MT system's outcomes. Consequently, the research relies on correlation framework validation and a two-sided equivalence test conducted on the sentiment classification outputs. Therefore, the experiment results may vary when different sentiment classification methods or evaluation methods are used.

Chapter 4. Development, Pre-processing, Implementation of Financial Text

4.1 Introduction

This chapter presents and describes the development, preprocessing, and implementation of the Arabic and English financial disclosures used in the current research. The objective of this chapter is to employ the ArFinSD in dictionary-based sentiment analysis across different analysis settings. Building upon the methodological frameworks outlined in Chapter 3, this chapter details the data foundations, the natural language pre-processing steps, and the analysis frameworks implemented for cross-language and cross-dictionary sentiment analysis.

The first part of the chapter provides a statistical overview of the datasets employed in the current research. It also addresses the textual data parsing, extraction, and preprocessing steps, which pose unique challenges due to Arabic's rich morphology and limited NLP resources compared to those of English. In this regard, the chapter provides details regarding Arabic NLP techniques and tools employed in the research and integrates relevant literature concerning textual data processing strategies. It further details the dictionary-based analysis implementations and specifications for the Arabic and English financial disclosures. The chapter documents the NLP tools and pre-processing techniques employed in the analysis, including lemmatization, stop word removal, n-gram modeling, and negation handling, paying attention to the linguistic phenomena specific to Arabic.

The second part of the chapter outlines three main frameworks for comparative sentiment analysis. Firstly, the chapter addresses the cross-language consistency of sentiment analysis by comparing the original Arabic financial disclosures with their English counterparts, utilizing ArFinSD and the LM dictionary, respectively. Secondly, it outlines the pre-processing and comparison setup, enabling the research to evaluate the effectiveness of ArFinSD within the Arabic financial domain in comparison to the general Arabic lexicon. Lastly, this chapter provides details regarding the creation of an MT corpus and the pre-processing used to assess sentiment preservation in Arabic-English financial documents. The chapter concludes with a discussion of the methodological and technical limitations associated with NLP pre-processing tools, implementation strategies, and sentiment analysis settings.

The chapter is structured as follows. Section 4.2 presents the research textual datasets used for sentiment analysis, including statistical summaries such as word counts, document lengths, and language distributions. Section 4.3 outlines the construction of the corpus, text parsing, and the scope of extraction in both languages. Section 4.4 discusses the choice of Arabic NLP libraries and the pre-processing steps used in Arabic and English to prepare the text for sentiment classification. Section 4.5 presents the implementation of the dictionary-based sentiment analysis methodology for Arabic and English financial data. Sections 4.6, 4.7, and 4.8 describe the three sentiment analysis settings the research is conducting, including cross-language analysis, analysis of finance-oriented and general Arabic sentiment dictionaries, and analysis of the impact of translation on sentiment in finance texts. Section 4.9 discusses the methodological limitations and constraints during pre-processing and sentiment analysis. The chapter concludes with final remarks presented in section 4.10.

4.2 Description of Financial Textual Data

The research relies on two primary datasets comprising narrative financial disclosures from companies listed on the Saudi Stock Exchange (Tadawul)[18]: (1) board of directors' reports and (2) CEO letters. The textual data are collected from the official Tadawul website. All reports are available in both Arabic and English on the companies' public profiles and are submitted as PDFs. The financial disclosures utilized in this research are officially referred to as the board of directors' reports according to the Saudi Capital Market Authority's (CMA's) Article 86 of the Corporate Governance Regulation (CMA, 2023, p. 51). Despite the CMA's formal designation, the board of directors' reports serve as comprehensive annual reports that summarize the firm's financial performance, governance compliance, and outlook. Article 86 of the Corporate Governance Regulation states that "*the board's report shall include the board's operations during the last fiscal year and all factors that affect the company's businesses"* (CMA, 2023, Article 86, p. 51). It further outlines 42 specific disclosure items that publicly traded companies are required to address in their board of directors' reports. These reports are equivalent to US Form 10-K reports imposed by the US Securities and Exchange Commission (SEC). Accordingly, the research refers to board of directors' reports as annual reports to maintain consistent terminology with the broader financial reporting and finance sentiment analysis literature.

4.2.1 Annual Reports Dataset

The first dataset comprises 728 Arabic annual reports and their corresponding English versions spanning the period from 2018 to 2023. These reports were manually collected from the official Tadawul website and cover 21 sectors of the Saudi stock market. Table 4.1 presents descriptive statistics on the word counts of the annual reports in both languages.

[18] https://www.saudiexchange.sa/

Table 4.1 Summary Statistics of the Annual Reports

	Reports	Total words	Words per document				
			Mean	Median	SD	Min	Max
Arabic	728	6,055,504	8,318	6,427	6,306	436	44,092
English	728	4,874,688	6,696	5,406	4,728	384	33,148

This table presents summary statistics for 728 annual reports in Arabic and their corresponding versions in English. In Arabic, a word is defined as a sequence of at least two characters, whereas in English, a word is defined as a sequence of at least three characters. In addition, the summary statistics reflect the corpus size after applying the stop word removal and text cleaning pre-processing steps. The statistical summary of the initial extracted and pre-processing corpora are provided in Appendix B.1(a). The stop word lists employed in this research can be found in Appendix B.4.

4.2.2 CEO Letters Dataset

The second dataset comprises 274 CEO letters written in both Arabic and English. Similarly, these letters were obtained from the Tadawul website and manually extracted from the annual reports reported in Section 4.2.1. The CEO letters are extracted from the annual reports when available. Additionally, the CEOs' letters are available in Arabic along with their corresponding English versions. Table 4.2 presents a descriptive summary of the word counts of the CEO letters in both languages.

Table 4.2 Summary Statistics of the CEO Letters

	Letters	Total words	Words per document				
			Mean	Median	SD	Min	Max
Arabic	274	162,756	594	468	433	99	2,692
English	274	124,122	453	382	319	43	2,103

This table presents summary statistics for 274 CEO letters in Arabic and their corresponding versions in English. In Arabic, a word is defined as a sequence of at least two characters, whereas in English, the word is defined as a sequence of at least three characters. In addition, the summary statistics reflect the corpus size after applying the stop word removal and text cleaning pre-processing steps. The statistical summary of initial extracted and pre-processing corpora are provided in Appendix B.1(a). The stop word lists employed in this research can be found in Appendix B.4.

4.3 Construction of the Financial Corpus

The financial disclosure analyzed in this research, the annual report, is a formal regulatory document issued by publicly traded companies on the SSE yearly in Arabic and English. The annual report does not typically follow a structured format and allows considerable variation across firms and years. Companies publish their annual reports in PDF format, including sections ranging from introductory and strategic discussions to governance disclosures and annual financial statements. Although the CMA regulates the core contents of the annual report, their formatting and presentation of these contents vary widely. Article (86) of the CMA's Corporate Governance Regulations sets out the mandatory content of annual reports, including corporate governance disclosures, financial summaries, strategic plans, risk assessments, and forward-looking statements (CMA, 2023). However, the CMA does not prescribe a standardized format nor does it regulate the extent of additional voluntary information that firms provide.

In contrast to financial statements, which follow a globally recognized XBRL structure, annual reports allow for significant design flexibility, leading to variability in layout, section organization, information graphics, and text flow. XBRL is a unified structure that serves as an internationally standardized computer programming language for financial statements. Some countries extend their reporting regulations beyond the standardized financial statement practices to include the format and structure of annual reports. For example, US-based companies are mandated to follow a standardized structure for 10-K annual reports and to submit them in plain text format. These reporting regulations enable more effective automated textual analysis and text extraction (El-Haj et al., 2018). However, the CMA does not impose legislation on Saudi firms regarding the format or structure of their annual reports.

More critically, the Arabic language poses unique challenges to the systematic extraction of annual reports. The challenges of systematically extracting Arabic PDFs are well documented in the Arabic NLP literature (Faizullah et al., 2023; Kasem et al., 2025). One of the most widely used technologies for extracting PDFs is optical character recognition (OCR). The OCR involves multiple stages to automatically recognize the text and convert it into plain text. In Arabic, the shape of letters varies according to their position within the word (initial, medial, final, or isolated). This leads to higher error rates in the OCR's segmentation and recognition phases (Kasem et al., 2025). Moreover, the diacritics (e.g., shadda and sukoon) and vowel marks (Tashkeel) that appear below or above the word are often misidentified in the recognition phase, leading to misinterpretation of words and a loss of accuracy. Other challenges involve the root-based morphological pattern in Arabic, which requires OCR to distinguish between visually similar Arabic words that differ in vowel marks.

In addition to the challenges posed by the Arabic script and its rich morphological structure, OCR systems fail to capture the logical organization of annual reports, which often include tables, charts, and infographics. These layout elements disrupt the text sequence and frequently break sentence continuity, especially in documents with multi-column layouts or infographics. As a result, the output extracted by the OCR system is often semantically disjointed, structurally disorganized, and cannot be processed without intensive manual correction. Although dictionary-based sentiment analysis does not rely on the sequential structure of the text, because words are independently transformed into a count matrix, it remains essential to extract Arabic documents and their English counterparts to measure sentiment across Arabic and English and to assess the translation effect on sentiment. In addition, Arabic sentiment analysis relies on the lemma as an input rather than inflectional forms, thereby making the text's sequential structure essential during the disambiguation phase. The lemmatization process often requires contextual word order to disambiguate the text more accurately (discussed in Section 4.4.2).

Zmandar et al. (2023) encountered similar challenges when converting Arabic financial reports from PDF format to plain text suitable for their proposed model. They built a large financial corpus consisting of Arabic documents, including annual and quarterly reports, press releases, and economic news. The authors used the PDF2Text algorithm alongside Sejda OCR to extract the text. Because of the unique features of Arabic script, such as right-to-left text direction and diacritics, among other obstacles, the authors achieved an extraction success rate of only 40% with the PDF2Text algorithm alone. The remaining reports were converted using the Sejda OCR system, which showed limited accuracy and was especially time-consuming. The authors noted that low-quality reports, outdated Arabic fonts, and poor word spacing reduced document conversion rates. However, their main goal was to build an Arabic financial corpus for training a large language model, without focusing on the English versions of the reports. In contrast, the current study requires a precise representation of both Arabic and English reports. Alignment is crucial for performing sentiment analysis across the two languages and for identifying the textual sentiment of the original and translated texts.

4.3.1 Method and Scope of Text Extraction

Given the limitations associated with the systematic extraction of text, the research relies on a manual extraction approach to convert annual reports into plain text suitable for further textual analysis. Although manually extracting PDFs into plain text is time-consuming and labor-intensive, it was necessary to ensure accuracy and consistency across the Arabic and English reports. Manual extraction is a well-established practice in the Arabic NLP literature (Itani, 2018; Itani et al., 2017; Mustafa et al., 2024; Zmandar et al., 2023), particularly where high-performing tools such as OCR systems and text parsers remain scarce. The linguistic complexity of Arabic, including its rich morphology, script direction, character shaping, and diacritics, poses substantial barriers to the adaptation of automated extraction methods. These limitations often require manual correction and extensive data cleaning to prepare the text for sentiment analysis models. Furthermore, the manual approach is widely used in translation studies, where a manually aligned bilingual corpus is considered to be essential in constructing parallel datasets, especially for training and evaluating MT models. The current research builds on that basis by manually preparing Arabic and English annual reports to ensure structural and semantic alignment.

The study's manual extraction approach aligns closely with its core objectives. The extraction approach employed in the current study is based on three key considerations unique to the research's questions and objectives: the complexity of the annual report layout, the requirements of bilingual documents, and the assessment of the impact of translation on sentiment. First, manual extraction was the most practical and accurate method, considering the nature of the annual reports in this research and the limitations of Arabic NLP. Annual reports are often lengthy, containing both textual sections and non-textual elements, such as tables, charts, and infographics. The non-textual content disrupts automated parsing because the OCR system frequently misclassifies visual content and adds it to unrelated sections. The unstructured layouts, combined with the absence of standardized formatting across firms, make manual extraction the most feasible method for recovering the full-text narrative and accurately assessing textual sentiment in these reports.

Second, the manual approach was essential to establish parallel reports in Arabic and English. Because the research objective is to measure sentiment across both languages in annual reports, each Arabic report must match its English counterpart in content and structure. However, Arabic and English differ significantly in terms of word order, morphology, punctuation, and syntax. As a result, the inherent differences between the two languages pose a significant challenge for automated tools in maintaining accurate alignment during extraction. The manual extraction approach fully captured the narrative sections, enabling reliable cross-language sentiment analysis. Lastly, the research assesses whether translation alters the sentiment tone in financial disclosures. Achieving this objective requires a high representation of both the source and target languages to evaluate the potential sentiment shift introduced by the translation. Any misalignment or inconsistency between the two would introduce analysis bias and ultimately affect the sentiment comparison across the reports. Manual corpus construction enables the preservation of tone, structure, and narrative in both reports, all of which are essential to accurately evaluate sentiment preservation.

Furthermore, textual sentiment is superior in explaining financial narratives, reflecting the managerial tone and the firm's future direction. The vast majority of the annual report components are either quantitative data which primarily reflect past performance (e.g., financial statements) or regulatory compliance sections (e.g., board members' qualifications) which do not convey textual sentiment. The research scope of analysis relies on the textual content and tone of the financial disclosures, as they may contain aspects of the firm's current position and outlook that are absent from the financial statements and regulatory compliance sections. Narrative sections of the annual reports, such as the board director's letter, the CEO's letter, the MD&A report, the risk assessment report, and the future expectations section, contain valuable clues regarding the firm's trajectory and, therefore, gauging the sentiment of these narratives is crucial. More importantly, quantitative information in the annual report, such as financial statements, is typically prepared and approved by managers; however, they have limited influence over these statements as this information is highly regulated by accounting guidelines and principles. Conversely, narrative information enables managers to express their views on the firm's past performance and future expectations.

The research employs a partial extraction strategy focused exclusively on the narrative content within the annual report. In the extraction phase, I observe the regulatory body and the CMA's requirements for annual reports. According to Article 86 of the Corporate Governance Regulations, 42 mandatory disclosure items must be included (CMA, 2023). While regulatory standards govern the content of the annual report, firms express considerable flexibility in terms of how sections are titled, organized, and presented. I then observed a sample of 120 annual reports retrieved from the dataset. The research developed a set of criteria to extract relevant textual data from the reports and to exclude non-informative data. During the extraction phase, the research excludes tables, charts, and financial statements because they do not contribute to the textual sentiment. In addition, corporate governance compliance requirements, such as the names, qualifications, and attendance logs of the board of directors, are excluded. These sections are not only irrelevant to the study's scope but are also poorly formatted as they are attached to the report as scanned documents. These excluded elements in the reports affect the flow of the extracted text and its alignment with the English counterparts of the Arabic version. Additionally, non-textual elements, such as tables, charts, and infographics, are excluded from the extraction process because they do not convey a managerial tone and often are presented in non-transformative formats.

The extracted data include all narrative sections conveyed in the annual reports, including but not limited to the introduction, the chairman's message, the CEO's letter, business and firm overview, operational performance discussion, strategic objective, human capital strategy, risk management, risk factors report, future outlook and expectations, market conditions, and economic environments. In addition, the research creates a separate dataset of CEOs' letters extracted from annual reports. The extraction for both the Arabic and English versions of the annual report is conducted in a parallel manner to ensure consistency in text presentation. After extracting the data into plain text, a manual check was undertaken to ensure accuracy and alignment between the Arabic and English versions. In the final stage, the extracted annual reports and CEO letters are processed programmatically for downstream textual analysis.

4.4 Financial Textual Data Pre-processing

Textual pre-processing is a crucial foundation for performing any sentiment analysis task. Pre-processing involves a set of NLP techniques that transform raw textual data into structured representations suitable for classification. The current research applied the pre-processing pipeline separately to Arabic and English text due to the fundamental linguistic and morphological differences between the two languages. Although Python is the primary programming environment for processing both documents, the techniques and libraries employed were language-specific. Each language has a customized pre-processing pipeline designed to handle its unique characteristics and configurations before the sentiment classification. Python was selected due to its flexibility, comprehensive natural language processing capabilities, and extensive support for Arabic and English language processing.

4.4.1 Arabic Pre-processing Libraries

Over recent years, a variety of Arabic NLP libraries have been developed to address the diverse linguistic challenges and ambiguities associated with the Arabic language, including Stanford CoreNLP[19], Farasa[20], MADAMIRA[21], and CAMeL Tools[22]. The Stanford CoreNLP (Manning et al., 2014) is a multilingual Java library that provides selected packages for Arabic NLP tasks such as POS tagging, tokenization, and sentence splitting. An official Python interface is also available (Qi et al., 2018), providing official bindings to CoreNLP, in addition to neural implementations for selected components of their library (Obeid et al., 2020). In addition, the

[19] https://stanfordnlp.github.io/CoreNLP/index.html
[20] https://farasa.qcri.org/
[21] https://inventions.techventures.columbia.edu/technologies/arabic-language--CU14012
[22] https://nyuad.nyu.edu/en/research/faculty-labs-and-projects/computational-approaches-to-modeling-language-lab.html

Stanford CoreNLP processes raw text as input by applying a configurable sequence of annotators such as tokenization or POS tagging. Each annotator enriches the dataset by adding linguistic information to the final annotations. It is based on a pipeline approach that allows the toolkit to produce a comprehensive representation of the text and then select a set of annotators to include based on a specific analysis target. The annotation pipeline workflow makes Stanford CoreNLP adaptable across languages, including English, Arabic, French, Chinese, Spanish, and German. Although Stanford CoreNLP offers Arabic NLP tasks, it is notably limited in scope compared to other Arabic NLP libraries.

Farasa (Abdelali et al., 2016) is another well-recognized collection of Java-based libraries for Arabic NLP developed by the Qatar Computing Research Institute (QCRI). Farasa offers a range of NLP analyses, including POS tagging, parsing, diacritization, and segmentation. Farasa is known for its speed and fast morphological analysis because the tool is designed to segment text without computational complexity, such as sentence-level information, thereby reducing processing time. Instead, the Farasa approach uses an SVM-based segmenter to rank possible segmentations of a given word using a set of features and lexicons (Abdelali et al., 2016). These features account for the likelihood of stems, prefixes, suffixes, and their contributions. Hence, Farasa is noticeably faster than other available Arabic NLP tools, such as MADAMIRA (by ten times) and QATARA (by one hundred times), according to the experimental results reported by Abdelali et al. (2016). A notable drawback of the Farasa toolkit is its lemmatization model, which yields ambiguous outputs, thereby limiting its usability in certain NLP tasks.

MADAMIRA (Pasha et al., 2014) is another prominent Java-based Arabic NLP library that merges two earlier systems, MADA and AMIRA, into a single framework. The MADAMIRA toolkit offers NLP features, including tokenization, segmentation, lemmatization, POS tagging, and named entity recognition. The system is designed to support MSA and Egyptian dialects using analyzers such as SAMA and CALIMA-ARZ. The library applies a hybrid machine learning approach that utilizes SVMs with N-gram language models to perform morphological disambiguation and provide syntactic and lexical analysis for each. MADAMIRA processes each token by converting it to Buckwalter transliteration, then performing morphological analysis and ranking all possible interpretations to yield the most accurate morphological outcome. The tool supports multiple usage modes, including a command-line interface (CLI) and Java API. Due to its linguistic capabilities, high accuracy, and modular pipeline architecture, MADAMIRA is one of the most widely adopted Arabic NLP tools, particularly for morphological disambiguation and syntactic analysis. Although the old version of the library remains accessible, it is now part of Camelira (Obeid et al., 2022), which is reported to offer better performance and broader support for Arabic dialects.

A dominant Arabic NLP library is CAMeL Tools, an open-source Python Toolkit for Arabic natural language processing developed by the CAMeL Lab at New York University Abu Dhabi (Obeid et al., 2020). The CAMeL Toolkit is a comprehensive Python library that addresses the complexity and diversity of the Arabic language by providing computational approaches for processing MSA and several Arabic dialects. The toolkit supports a broad spectrum of essential NLP tasks, including pre-processing, morphological modeling, named entity recognition, dialect identification, and sentiment analysis. It also provides CLIs and application programming interfaces (APIs) to support its functionality.

Moreover, CAMeL Tools integrates various Arabic NLP projects developed within their lab at New York University, Abu Dhabi. For example, the library includes an early project, namely CALIMA-Star (Taji et al., 2018), one of the most comprehensive Arabic morphological analyzers and generators that is publicly available for unrestricted use. CALIMA-Star provides morphological functions, tokenization schemes, and morphological reinflection capabilities. This allows the CAMeL Tools to handle Arabic Text and perform complex lexical analysis, morphological disambiguation, lemmatization, and diacritization. In addition, the CAMeL tool continues to improve and expand its functionalities to serve broader research and Arabic NLP applications. As evidence of CAMeL Tool advancement, the toolkit has been extended through various new applications, such as Camelira, a multi-dialect morphological disambiguator (Obeid et al., 2022), CAMeLBERT, a transformer-based module designed to process Arabic text (Inoue et al., 2021), WildDiacs, a diacritization patterns algorithm (Elgamal et al., 2024), and CAMELMORPH MSA, a large open-source morphological analyzer (Khairallah et al., 2024). With its comprehensive coverage, CAMeL Tools serves as a complete toolbox suitable for various Arabic NLP projects[23].

4.4.2 Arabic Text Pre-processing Pipeline

The research utilizes the CAMeL Toolkit to process Arabic textual data, performing several pre-processing steps necessary for sentiment classification. The CAMeL Toolkit provides all of the necessary Arabic NLP pre-processing steps that align with the research framework and

[23] See Elgamal et al. (2024) for tokenization, diacritization, and morphological analysis; Alhafni et al. (2023) for morphological analysis; Al Qabani & Kurdy (2022) for POS tagging, lemmatization, and named entity recognition; Alhafni et al. (2022) for gender identification and morphological disambiguation; Hakami et al. (2021) for sentiment analysis and dialect identification; Alrayani et al. (2024) for sentiment analysis; Salesky et al. (2021) for diacritization; Gaser et al. (2023) for normalization; Alshammari et al. (2024) for dediacritization; Moussa & Mourhir (2023) for tokenization.

objective. Scholars differentiate between Arabic text mining for MSA and for informal text and dialects. MSA text tends to be more structured and less noisy than informal text. However, despite the goal of text mining, data preparation and pre-processing are critical. An effective pre-processing method can eliminate 30% to 50% of the initial features, retaining only the most relevant features associated with the target value (Gaye et al. 2021). The proposed pre-processing framework in the current research is designed to enhance the accuracy of the dictionary-based sentiment analysis.

Initially, the text was lightly normalized to ensure orthographic consistency and eliminate noise in the data. Normalization is a fundamental step in text mining that converts text into a consistent, standardized form to reduce data noise. Even though the financial textual data in this study is classified as an official medium of communication and composed in MSA, the data still require normalization due to the nature of Arabic and the annual report's original formats. Arabic official texts tend to be less noisy than informal or Arabic dialect texts, such as social media content. Common textual phenomena observed in social media data, such as duplicate words, repeated letters, or elongated words (Tatweel), are rare in the annual report dataset. As a result, only limited pre-processing steps are required at this stage. In the normalization phase of the study, two steps are applied relying on the CAMeL Tool library to standardize the Arabic financial text, including:

1. Unicode normalization: This step ensures that the text is represented in a standardized Unicode form. Despite manual extraction, inconsistent character encoding may occur due to different fonts and formatting. In some cases, characters have identical visual forms but differ at the byte level.
2. Tatweel character removal: This is primarily used on elongated words (e.g., the Profit: الأربـــاح converts to الأرباح). Despite Arabic words having the same semantic value, elongation affects the accuracy and recognition of the tokenization and lemmatization algorithm.

Although the annual reports are written in MSA, which avoids elongated word forms, Tatweel character normalization was necessary for the data. The manual inspection revealed limited occurrences of Tatweel, introduced either by the firm for layout purposes in the initial PDF files or by font encoding issues during extraction. While these elongated characters serve no linguistic function, they affect the following pre-processing techniques where word-structure consistency is critical. The normalization procedures are essential to optimize the performance of tokenization and the morphological disambiguator while preserving the text's syntactic and semantic structure.

Next, the research employs lemmatization to transform Arabic text into a normalized form of words, reducing morphological variability. A lemma is known as ‘the look-up form,’ which contains all possible inflected forms of the word. Arabic words are highly inflectional, exhibiting substantial morphological variability, severely undermining the feasibility of conducting dictionary-based sentiment analysis relying on original (unprocessed) word forms. Hence, the proposed ArFinSD in this research is based on lemma entries to ensure effective word identification. Therefore, the Arabic annual reports and CEO letters are subject to lemmatization to enable alignment with the proposed sentiment dictionary.

Lemmatization is conducted through a morphological disambiguation process, which is defined as the process of selecting the correct analysis for a word based on its context (Yildiz et al., 2016). The morphological analyzer provides a set of linguistic information for each word, including POS tagging and verb tense. The limits of the semantic and syntactic features produced by the morphological analyzer are flexible and determined by its linguistic capabilities. Lemmatization is a subcomponent within the morphological disambiguation algorithm where each word’s dictionary base form (lemma form) is identified and extracted. Consequently, an accurate morphological disambiguation analyzer determines the accuracy of the word’s lemma. The morphological disambiguation and lemmatization are core linguistic techniques for the research’s Arabic sentiment analysis framework. Therefore, selecting the appropriate morphological disambiguation model is highly critical, given that the model analysis’s output is employed in a dictionary-based sentiment analysis to determine the tone in the financial disclosures.

Due to the linguistic complexity of Arabic, morphological disambiguation is a critical component of Arabic text processing in all major Arabic NLP libraries, including Farasa, MADAMIRA, and CAMeL Tool. Although the Stanford CoreNLP toolkit was considered in the early pre-processing steps, the library lacks a lemmatization model. These libraries support MSA because each library trains, evaluates, and designs its analysis model around MSA corpora. MSA corpora usually include detailed annotations for multiple linguistic levels, such as morphological analysis, POS tagging, and syntactic annotation, which play significant roles in the training and accuracy assessment phases. Given the language of the financial documents under study, the shared support of MSA across these libraries is essential. Theoretically, they are well-suited for disambiguating and lemmatizing annual report documents because they are written in MSA, a formal style used in official disclosures and communications. However, the performance of these tools varies significantly in terms of accuracy, efficiency, and contextual robustness, especially when applied to domain-specific texts, such as annual reports.

In asserting the accuracy and performance of the disambiguation analyzers, researchers rely on annotated corpora that offer a set of linguistic levels. A prime example is the Penn Arabic Treebank (PATB) which has been heavily utilized to evaluate morphological analysis modules. PATB is a well-established MSA corpus developed and annotated by the Linguistic Data Consortium (LDC) at the University of Pennsylvania (Maamouri et al., 2004). Additionally, the comparison between models usually includes key linguistic tasks such as morphological feature prediction, lemmatization, POS tagging, and diacritization accuracy, as well as tokenization; however, it is not limited to these because additional NLP features may also be considered.

The developers of the CAMeL tool (Obeid et al., 2020) conducted a comparative evaluation of their model's performance against MADAMIRA across several Arabic NLP features, using the PATB corpora parts 1, 2, and 3. The assessment focuses on lemmatization, POS tagging, full morphological feature accuracy, diacritics, and tokenization. The CAMeL tool comprises two modules: the multitask learning system and maximum likelihood estimation (MLE). The results indicate that the multitask model achieved competitive performance, outperforming MADAMIRA in terms of diacritic accuracy (90.9% vs 87.7%) and POS tagging (97.2% vs 97.1%). The multitask model scored 95.4% in the lemmatization analysis, slightly below MADAMIRA's 96.4%. CAMeL's multitask model achieved 89.0% for the full morphological feature accuracy, whereas MADAMIRA scored 85.6%. In contrast, the MLE model demonstrated a slightly higher lemmatization accuracy of 95.7% than the multitask model. The MLE model lagged in terms of diacritic accuracy (78.4%) and full morphological feature accuracy (70.0%). Tokenization accuracy is consistently high across all models, with CAMeL's multitask model achieving 99.4%, marginally ahead of MADAMIRA and MLE (both at 99.0%). It is worthy of note that the MADAMIRA morphological analysis model is trained on the same dataset (PATB) used for evaluation. The CAMeL Tool, in contrast, was developed using various resources and predefined lexical dictionaries, including CALIMA-Star (Taji et al., 2018), to construct the morphological analyzer.

Nonetheless, the MADAMIRA Tool has been reported to outperform CAMeL in terms of lemmatization while underperforming in POS tagging analysis accuracy under different evaluation settings. For example, Hammouda et al. (2024) introduced SinaTools, a new Arabic NLP library, and conducted a benchmark comparison against several NLP libraries, including CAMeL, Farasa, and MADAMIRA. The authors conducted the assessment using PATB corpora and the Salma dataset. The study created two scenarios in the lemmatization assessment: (1) with the exact lemma spelling and (2) after eliminating numbers from the lemmas. Their evaluation indicated that MADAMIRA achieved lemmatization (without numbers) F1 scores of 88.3% (PATB) and 86.6% (Salma), whereas CAMeL Tools achieved 80.9% and 81.7%, respectively. In addition, the authors evaluate POS tagging using 18 and 40 tags. Part-of-speech tags are labels assigned to words or tokens to reflect their linguistic and semantic features. The results showed that, across the 40 tags, MADAMIRA achieved POS tagging F1 scores of 82.3% (PATB) and 80.2% (Salma), whereas CAMeL Tools achieved 82.7% and 81.6%, respectively. Similar results were observed in the POS 18-tag evaluation, with the CAMeL tool showing a slight edge over MADAMIRA.

Furthermore, the evaluation shows that Farasa consistently underperformed CAMeL Tools across lemmatization and POS tagging features. Farasa did not report scores under the proposed evaluation settings in the lemmatization assessment. The authors noted that Farasa returns forms without diacritization or sufficient contextual disambiguation, which do not align with the gold-standard references used for the evaluation. The ambiguity in Farasa is inherent in their system because the lemmatizer consistently returns forms without diacritization. For example, the words (تَحَدِّي) and (تَحَدَّى) represent two distinct lemmas; the former functions as a noun (challenge), whereas the latter reflects the verb form (he challenged). Under the Farasa lemmatizer, both forms are returned as diacritized values (تحدي) which hinder the disambiguator's ability to distinguish between the lemma entries within the sentiment dictionary and the financial text. Such a limitation in the Farasa undermines its lemmatizer's capabilities in dictionary-based analysis where accurate lemma representation is critical in the sentiment classification phase because semantic distinctions between similar words can affect classification accuracy.

The disparity between CAMeL and Farasa Tools is more noticeable in the POS tagging evaluation. When assessed using the full 40 tags, CAMeL Tools achieved F1 scores of 82.7% (PATB) and 81.6% (SALMA), whereas Farasa achieved significantly lower scores of 62.4% and 62.8%, respectively. Even under the smaller set of 18 tags, CAMeL maintained high scores of 91.9% (PATB) and 87.0% (SALMA), compared to Farasa's 84.9% and 82.7%. These results reflect CAMeL's superior performance in morphological disambiguation and POS tagging, making it a more accurate and reliable tool for processing MSA text.

Similarly, Alluhaibi et al. (2021) conducted a comparative evaluation focused exclusively on POS tagging performance using text samples from literary Saudi novels. The study evaluates the performance of five Arabic POS taggers, including CAMeL and MADAMIRA, and Farasa, applying a more simplified tag set consisting of verb, noun, adjective, and others (all other POS types). The authors emphasize that although CAMeL and

MADAMIRA generally exhibit comparable performance on MSA newswire text, such as in the PATB corpus, their performance varies when applied to literary text. In this evaluation, MADAMIRA achieved a higher average F1 score of 88% than CAMeL's 84%, with a notable gap reported in the adjective category due to CAMeL's lower recall score. They argue that the discrepancy between their evaluation and that reported by Obeid et al. (2020) (97.1% vs 97.2%) is due to their use of CAMeL's MLE disambiguation model rather than the multitask learning model used in Obeid et al.'s evaluation. However, Obeid et al. (2020) reported POS tagging accuracies of 97.1% for MADAMIRA and 95.5% for CAMeL's MLE disambiguation model, indicating that the multitask learning model used in their evaluation achieved slightly lower accuracy than MADAMIRA.

Farasa, on the other hand, achieved a slightly higher average F1 score than the CAMeL Tool (86% vs. 84%). In particular, it outperformed CAMeL in the adjective (74% vs. 64%) and 'other' (80% vs. 70%) categories, whereas both tools performed similarly on noun and verb categories. However, the evaluation is conducted on textual data comprising the Saudi novel, expressed in MSA and Saudi dialects. These narratives differ significantly from those in the annual reports, which can affect the POS tagging. Although lemmatization accuracy is not directly evaluated in this evaluation setting, Farasa operates on a simplified POS tag set and does not fully return diacritized lemma forms. This leads to ambiguous output, affecting the dictionary-based analysis identification accuracy. Therefore, the Farasa toolkit remains unsuitable as a lemmatization model for handling financial MSA text.

Nevertheless, it is worthy of note that the findings reported by Alluhaibi et al. (2021) contradict those of Hammouda et al. (2024), who evaluated CAMeL and Farasa under different conditions. While Alluhaibi et al. found Farasa to slightly outperform CAMeL in POS tagging based on a small corpus of Saudi novels, Hammouda et al. found that CAMeL consistently achieved greater accuracy than Farasa across well-established MSA corpora (PATB and SALMA), especially under the 40-tag evaluation. The PATB corpus consists of 339,710 tokens, whereas the SALMA dataset includes 34,253 tokens and both have been semantically and morphologically annotated. The observed discrepancy may be attributed to variations in the corpus type, domain, size, and POS tagging annotation. In Alluhaibi et al.'s (2021) evaluation setting, the authors relied on narrative text from novels containing dialectal variation. In contrast, Hammouda et al. (2024) relied on extensive, standardized benchmarks widely adopted in the Arabic NLP literature. These differences suggest that Farasa's advantage stems from its suitability for informal narratives with simplified tagging requirements, whereas the CAMeL Tool demonstrates strong robustness and tagging precision in formal narratives.

Among these libraries, the CAMeL Tool demonstrates competitive performance in morphological disambiguation and lemmatization. CAMeL's disambiguation analyzer demonstrates robust morphological analysis. It also provides a comprehensive set of NLP features, directly aligned with the research framework for processing Arabic textual data, including normalization, tokenization, morphological disambiguation, and lemmatization. All of these pre-processing steps are conducted within a unified Python-based ecosystem, which minimizes analysis complexity by accounting for the scale of the textual data under study. In addition, each NLP feature provided by the CAMeL Tool and employed in the research framework has been extensively used in the Arabic NLP literature and has demonstrated its ability to handle various NLP tasks (see footnote 6). More precisely, the disambiguation models offered by CAMeL Lab provide comparative results for both models.

Employing CAMeL through a Python-based ecosystem facilitates seamless integration with the English textual analysis pipeline, enabling efficient sentiment analysis across both languages. The research framework involves performing dictionary-based sentiment analysis in both languages and examining the impact of translation on sentiment. A Python-based ecosystem enables consistent and efficient implementation of the bilingual sentiment analysis framework developed in this research. Furthermore, the CAMeL library's free availability and continuous updates with new models, as demonstrated by the most recently added modules, attract more scholars and help to build strong community support. In addition, MADAMIRA is now part of another CAMeL Lab project, the Camelira (Obeid et al., 2022), which offers broader coverage and better performance. The Camelira is a multi-dialectal morphological analyzer with a web interface that enables users to search for linguistic information about Arabic words. Although the developers (Obeid et al., 2022) reported that the model would be available in the CAMeL Tool, it was neither publicly available nor included in their library at the time the current research was conducted.

Furthermore, the CAMeL disambiguation approach provides extensive and detailed morphological analysis. The analyzer annotates words with a range of morphological features, including gloss, stem, POS tagging, gender, mood, number and, most importantly, the lemma form. The morphological analyzer in the CAMeL tool produces more than 30 features, including core grammatical features, clitic-related features, and lexical-orthographic features[24]. The CAMeL tool offers a superior level of comprehensive and detailed linguistic analysis compared to other available libraries. Accordingly, the research systematically leverages its

[24] For a comprehensive view of all features, visit the CAMeL tool morphology documentation at https://camel-tools.readthedocs.io/en/latest/reference/camel_morphology_features.html

morphological features across multiple phases. For example, the research utilizes the orthographic feature provided by the CAMeL tool, namely Buckwalter Arabic transliteration, to convert sentiment word format into standardized Arabic lemma entries. The sentiment entries transformation enables the research to align the ArFinSD with the ArSenL general sentiment dictionary, which has been employed in the research's sentiment analysis framework (discussed in Section 4.7.1). Overall, CAMeL's integration of lexicon-driven disambiguation, broad tag coverage, and robust MSA compatibility ensures better alignment with the requirements of financial text preprocessing, where morphological clarity and consistent POS are critical in dictionary-based analysis.

To implement the lemmatization, the research employed CAMeL's MLE disambiguation to extract the lemma forms of the annual reports and CEO letters. As Obeid et al. (2020) described, the MLE disambiguator relies on a rule-based analyzer supported by predefined lexical probabilistic scores built upon the CALIMA-Star framework (Taji et al., 2018). The CALIMA-Star extends earlier works, such as the BAMA (Buckwalter, 2002) and ALMORGEANA (Habash, 2007) databases. These databases contain three predefined lexical tables, including prefixes, stems, and suffixes, and leverage three compatibility tables structured as prefix-suffix, prefix-stem, and stem-suffix, ensuring morphologically valid combinations. The CAMeL disambiguator generates all possible out-of-context morphological analyses of a given word with features such as lemma, POS, gloss, gender, number, and case. The disambiguator then ranks the content analyses of a token and selects the most probable interpretation through the scoring combination. It is important to note that the multitask learning system has not been made publicly available and is not included in the CAMeL Tools library. Instead, CAMeL's library performs disambiguation through either the MLE or BERT models. The research conducted a parallel analysis using the extracted annual reports with both models and observed no difference in sentiment classification accuracy (see Appendix B.2 for further details).

In addition, during the pre-processing phase, the research considers stemming as an alternative approach to lemmatization. Stemming further reduces the word to its base root, which introduces substantially more inflectional and derivational forms to be clustered under a stemmed word. However, due to the Arabic language's inflectional and derivational system, such as the three-letter root, distinct sentiment words are grouped into a single stem form. This behavior, whilst it may be beneficial for various NLP tasks, dramatically reduces the sentiment classifier's accuracy by grouping unrelated sentiment words under a single stem. Appendix B.3 provides further details on the sentiment analysis results using stemming as an alternative approach, demonstrating that lemmatization is significantly more accurate as a word representation for Arabic dictionary-based sentiment analysis.

After the lemmatization phase has been conducted on the Arabic annual reports and CEO letters, parallel lemmatized versions of these datasets are established and used for further pre-processing, ultimately enabling sentiment analysis. Table 4.3 illustrates how lemmatization effectively clusters several inflected forms in the annual reports and CEO letters into a single lemma.

Table 4.3 Lemma-based matching of Morphological Variants in Arabic Annual Reports

No.	Lemma	Morphological variants	English translation
1	تَطْوِير	وتطوير; لتطوير; والتطوير; تطوير; بتطوير; وتطويره; تطويرها; والتطويرات; تطويري; فالتطوير; وتطويرهم; تطويرية; وتطويرهما; لتطويرهم; فتطوير; كتطوير; فتطويرهم; لتطويرهما; وتطويرهن	improvement enhancement
2	مُؤَقَّت	المؤقتة; مؤقت; المؤقت; مؤقتة; مؤقتا; المؤقتين; مؤقته; والمؤقتين; المؤقته; والمؤقت; بمؤقتات; مؤقتين; ومؤقت; مؤقتات	tentative
3	فَعّال	الفعال; فعال; وفعال; فعالة; الفعالة; وفعالة; فعالا; وفعالا; وفعالي; الفعالين; لفعالي	efficient influential
4	تَخْفِيض	وتخفيض; تخفيض; التخفيض; بتخفيض; لتخفيض; التخفيضات; تخفيضه; تخفيضات; تخفيضها; كتخفيض; وتخفيضات; للتخفيض; والتخفيضات; كالتخفيض; تخفيضا; بتخفيضها; وللتخفيض; بالتخفيضات; كتخفيضها; وتخفيضه	downgrade downsize
5	صُعُوبَة	الصعوبات; صعوبات; صعوبة; والصعوبات; لصعوبات; الصعوبة; وصعوبة; لصعوبة; للصعوبات; بالصعوبات; وصعوبات; والصعوبة; بالصعوبة; للصعوبة; بصعوبة; صعوبتها	difficulty aggravation complication
6	تَراوَح	تتراوح; يتراوح; وتتراوح; تراوحت; ويتراوحو; وتراوحت; لتتراوح; ليتراوح	varies
7	إِنْجاز	إنجاز; الإنجاز; الإنجازات; إنجازات; والإنجازات; بالإنجازات; إنجازاتنا; وإنجازاتها; لإنجاز; وإنجازات; وإنجاز; الانجازات; إنجازاتها; والإنجاز; إنجازه; بإنجازات; وإنجازاتهما; للانجازات; فالإنجازات; بانجازاته; بإنجازاتهن; انجازاتهم; إنجازين; وإنجازنا	progress success accomplishment achievement attainment breakthrough

The table illustrates the process of lemmatization applied to the morphologically distinct Arabic forms. The analysis is conducted using morphological disambiguation within the CAMeL Tool (MLE model). Although each form varies in affixes and syntactic function, it is grouped back to a unified lemma. The English translations correspond to the lemma according to the ArFinSD and the LM entries. The translations correspond to all morphological variants for each lemma.

In the final step, the research addresses stop words in the financial narrative. Stop word removal is a fundamental pre-processing technique in NLP and sentiment analysis and its purpose varies significantly depending on the specific NLP application. Stop words are frequently occurring words in a corpus with minimal semantic content; they serve a syntactic function without affecting the subject matter (El-Khair, 2006). As a result, when determining sentiment polarity, grammatical words such as prepositions, conjunctions, particles, and pronouns do not carry sentiment. Other NLP applications, such as information retrieval, text summarization, and MT, employ stop word removal for different purposes. For example, in an information retrieval system, stop word removal increases query efficiency by removing common words that do not convey semantic meaning when matching a query to a relevant document.

The importance of stop word removal stems from the fact that, in dictionary-based sentiment analysis, these words introduce noise and affect sentiment measurement at the document level. Stop words tend to be used extensively in the corpus because they serve critical syntactic functions within the sentence's grammatical structure. Consequently, the unnecessary insertion of these high-frequency, non-informative terms into the sentiment-scoring process increases the term-document matrix with no added value. However, since the research relies on morphological disambiguation models to identify the lemma forms of the text, the stop words are identified after the disambiguation phase. This is because the sentiment classification accuracy depends on the disambiguation analyzer's accuracy, which is inherently trained on various corpora and models. For example, the CAMeL MLE model is structured to disambiguate words regardless of context, ranking all possible analyses and assigning the best analysis for each token based on the predefined lexical dictionary. In contrast, the CAMeL BERT disambiguator is context-aware, in which the model determines the token analysis based on the word's syntactic and semantic attributes. In that regard, keeping the corpus as structured as possible arguably produces more accurate morphological token analysis.

The emphasis on preserving syntactic structure aligns with an early effort in the literature to improve lemmatization accuracy. Al-shammari and Lin (2008) proposed a novel Arabic lemmatization algorithm that considers syntactic and morphological aspects of the text to overcome the limitations of traditional stemming approaches, such as over- and under-stemming. Instead of immediately applying stop word removal, the authors distinguished between useful and useless groups. The useful stop words, which include words that typically precede nouns and verbs, were initially retained to enhance POS identification and lemmatization processes. The other group contained words that do not provide syntactic or semantic information during lemmatization. The authors showed that delaying the removal of stop words can enhance the accuracy of POS tagging and reduce stemming errors, thereby improving the quality of the text normalization process. Although the authors focus on lemmatization accuracy as part of the normalization preprocessing steps, their approach encourages delaying stop word removal to achieve more precise lemmatization, which is critical for reliable sentiment analysis in this research. To address this issue, the research uses a predefined, lemmatized list of stop words to identify these non-informative words and exclude them from further consideration in sentiment classification.

To that end, a major challenge in Arabic NLP is the lack of standardized stop word lists that are suitable across multiple domains and dialects. Although several efforts have been made to bridge this gap, these resources are often established to address specific dialects, such as Egyptian or Gulf Arabic, or to address general informal Arabic text data resources. The lack of standardized stop word lists is demonstrated in the Arabic sentiment analysis literature, where researchers construct custom stop word lists manually for specific domains or datasets of their sentiment analysis tasks (Duwairi et al., 2014; El Kah & Zeroual, 2021; Medhat et al., 2015; Musleh et al., 2023; Nassr et al., 2021; Oussous et al., 2019). More importantly, what constitutes a stop word is often task-dependent. In the context of Arabic sentiment analysis for finance-oriented texts, no Arabic stop word list is available that aligns with the research's design and scope.

To address the lack of finance-oriented stop word lists in Arabic, the research implemented domain-oriented stop word lists based on two primary resources. First, the study employed the English stop word lists obtained from official Loughran-McDonald dictionary resources[25], including Geographic, Date and Number, Currency, Currency Abbreviation, Financial Job Title, and Generic Word. Second, the research introduced three custom Arabic stop word lists, explicitly designed for the research's scope and dataset characteristics: Geographic, Long Company Names, and Short Company Names. These additional stop word lists are established to address Saudi Arabia's geographic location and its market-traded companies. In addition, the research compiled and utilized equivalent stop word lists in both Arabic and English to ensure consistency across both languages in the sentiment analysis. All stop word lists were bidirectionally translated to ensure linguistic equivalence across the textual datasets, thereby maintaining consistency across languages (see Appendix B.4). To match the lemmatized annual reports and CEO letters, the Arabic stop word lists were lemmatized using the same approach as the financial text.

At this stage, the Arabic textual data is fully pre-processed and prepared for sentiment analysis. The statistical summaries of the textual datasets in Table 4.1 and Table 4.2 reflect the datasets after the full implementation of the pre-processing stages detailed in the preceding

[25] https://sraf.nd.edu/textual-analysis/

sections. Complementary statistical summaries of the textual datasets are provided in Appendix B.1 (a-1) and B.1 (a-2), detailing the raw data from the PDF extraction as tokens, as well as the data from the pre-processing stage before stop-word removal. Upon completing the pre-processing steps, the Arabic dataset is fully prepared and suitable for dictionary-based sentiment analysis.

4.4.3 English Text Pre-processing Pipeline

This section outlines the pre-processing steps applied to the English textual datasets, including the English version of the annual reports and the CEO letters. Pre-processing the English text requires fewer preparation steps because it is less linguistically challenging and involves a more straightforward sequence of steps than Arabic text. However, the alignment of English and Arabic textual data remains critical to answering the research questions and achieving the research objectives.

In handling the English textual data, the research relies on Python due to its rich ecosystem in terms of available NLP tools and, more importantly, its seamless integration with the Arabic textual data and sentiment classification framework. The English texts were processed using the Natural Language Toolkit (NLTK; Bird & Loper 2004)[26], one of the predominant NLP libraries that provides extensive support for text processing, including tokenization, POS tagging, stemming, and lemmatization, among other NLP features. NLTK's flexibility allows for performing all necessary pre-processing steps on English text. In addition, employing NLTK within the research framework ensures easy integration with the sentiment analysis pipeline and maintains consistency across both languages' proposed frameworks.

The corpus preparation steps, including data extraction, formatting, and alignment, are identical to those used for the Arabic textual data. The English reports were manually extracted from PDF format and converted into plain text, following the approach illustrated in Sections 4.3 and 4.3.1. The extraction approach ensures consistency in narrative content across the Arabic and English versions, enabling accurate cross-sentiment comparison. Preserving the textual semantics and structure of the annual reports is crucial to measure the tone across both versions of the financial documents. More importantly, the English text does not require extensive normalization. This is due to the regularity of orthographic and morphological aspects of the English language, which allows for conducting dictionary-based sentiment analysis using the original base form of the text.

[26] The official website for NLTK is https://www.nltk.org.

Therefore, the research does not apply further normalization to the English text and keeps the text in its original surface forms, following the approach proposed by Loughran and McDonald (2011). The LM sentiment dictionary is based on word inflections, arguing that inflection-based sentiment dictionaries enhance accuracy in capturing sentiment by avoiding further normalization, such as stemming (Loughran & McDonald, 2011). Equally, the accuracy of inflection forms compared to stemmed forms has been confirmed by Bannier et al. (2019) who conducted textual analysis using the LM dictionary and a stemmed version of the same dictionary. The authors reported that inflectional forms are more accurate at capturing sentiment than stemming because reducing a word to its root or stem can lead to misclassification of sentiment. The research considers an alternative approach to word representations, such as stemming, in dictionary-based sentiment analysis. It confirms earlier findings by Loughran and McDonald (2011) and Bannier et al. (2019) that inflected words provide more accurate sentiment classification (see Appendix B.3 for further details). Thus, the English text was processed using minimal normalization and cleaning techniques to preserve the original words for sentiment matching.

To prepare the English text for sentiment classification, I apply lowercasing to convert all characters in the text into uniform cases. This step is necessary to ensure sentiment word matching between the corpus and the sentiment dictionary because entries are case-sensitive. This is followed by punctuation removal, eliminating characters such as commas and periods that do not convey or alter sentiment. After text normalization, tokenization is applied to segment the text into tokens that reflect the basic components of sentiment classification. Subsequently, as in the Arabic pre-processing step, stop word removal was applied. The English stop word lists were obtained from official LM dictionary resources. The research further establishes English versions of the Arabic stop word lists, designed to address the research's specific textual data. The stop word lists are reported in Appendix B.4(b). The statistical summaries presented in Table 4.1 and Table 4.2 reflect the English textual dataset after all pre-processing steps have been completed. Appendix B.1(a-1) and B.1(a-2) offer complementary statistical summaries of the textual datasets, including raw data from the PDF extraction in token form and data from the pre-processing stage before stop word removal.

4.5 Implementation of Financial Text Sentiment Analysis

This section presents the methodological framework used for dictionary-based sentiment classification of Arabic and English financial texts, including annual reports and CEO letters. Although the classification approaches for Arabic and English texts are implemented based on each language's linguistic structures and sentiment word representations, the textual sentiment classification remains consistent in both languages through the framework of BoW classification. Dictionary-based sentiment classification relies on the lemma-based ArFinSD established in this research, which categorizes sentiments into positive, negative, and uncertain categories. The English financial documents were classified using the LM dictionary, utilizing the positive, negative, and uncertain word lists. Table 3.1 provides the number of words in each sentiment category across the ArFinSD and LM dictionaries.

The research develops a custom Python function to detect sentiment words in annual reports and CEO letters. The classification function in Arabic text relies on rule-based n-gram modeling that considers unigrams, bigrams, and trigrams to recognize single-word and multi-word sentiment expressions. For English text, the dictionary-based function only applies a unigram matching schema because the LM includes only one-dimensional word representations. Furthermore, the classification framework incorporates a negation-handling algorithm for both Arabic and English texts, which identifies predefined negation forms and reverses the sentiment polarity within a three-word contextual window. This implementation aims to enhance sentiment classification accuracy by ensuring that predefined sentiment words are interpreted when negation forms are processed. The results of this implementation provide a comprehensive set of linguistic frequency counts which are used to calculate the share of the sentiment words and the overall sentiment score *(Tone)* for each annual report and CEO letter at the document level.

4.5.1 Sentiment Analysis for Arabic Financial Text

Because the Arabic textual data are lemmatized and tokenized, each word is treated as a separate token, enabling dictionary-based sentiment analysis. A custom sentiment classification function is established using a rule-based word list approach specific to the research's framework and sentiment identification. Relying on the ArFinSD, the classifier processes each token and systematically maps it to one of several predefined sentiment and linguistic categories. These categories include lists such as positive, negative, uncertain, negation, not-word, and stop word classes.

The function first generates unigrams, bigrams, and trigrams from the tokenized text. The multi-layered structure allows the model to capture single-word and multi-word sentiment expressions. More importantly, the classification function follows a hierarchical prioritization scheme in which trigrams are processed first, followed by bigrams and finally unigrams. Unigrams serve as a fallback within the function when neither trigrams nor bigrams match the entries in the sentiment dictionary. The classification function enables the matching of two- and three-dimensional words with ArFinSD wordlists, removing them from further consideration in the rule-based function before proceeding to match one-dimensional words. As a result, longer dimensional words are prioritized and captured, thereby avoiding redundant sentiment overlap. The sentiment classification for Arabic text then assigns n-gram matches to each sentiment category.

After constructing the n-gram sets, the classifier filters and cross-references each category set against its respective sentiment dictionary. Accordingly, if a match is identified, the sentiment label is assigned. Tokens or n-grams in the text that do not appear in any predefined lists are labeled as 'none.' In contrast, tokens with fewer than two characters are considered non-informative and excluded from the sentiment classification. In Arabic textual analysis, a word is defined as a sequence of at least two characters. Consequently, the filtering step ensures that only sentiment words contribute to the final sentiment assessment.

In addition, the classification function includes a negation-handling algorithm based on predefined Arabic negation forms and a three-word negation scope window. The function considers a forward-looking window of three tokens when one of the negation forms (لا-Laa, ليس-Laysa, لن-Lan, لم-Lam, بلا-Bla, دون-Dwn, غير-Gyr, عدم-Edm, عكس-Eks) is identified. The function scans the window to locate predefined sentiment words, including positive and negative lists, and if the classifier successfully locates a sentiment entry, the polarity is flipped accordingly. For example, a positive sentiment word preceded by a negation form is reclassified as 'negated-positive.' The negated classes (negated-positive and negated-negative) are treated and counted independently to distinguish them from direct sentiment matches. Nonetheless, these classes are reconsidered and reclassified according to their new sentiment category, accounting for the negation effect in the final sentiment classification. The negation polarity-flipping effect of sentiment words is considered at the final step and added to the respective sentiment categories to enable the assessment of the classifier's effectiveness in incorporating the negation algorithm into the overall sentiment assessment.

Following the sentiment classification, I employed Python to generate a sentiment frequency matrix for each annual report and CEO letter. The documents were converted into a structured sentiment vector word count based on the dictionary-based methodology framework. Each unique token is assigned to a sentiment label (e.g., positive, negative, uncertain, negated-positive, negated-negative, or none). In addition, the frequency of the unique token within the documents is recorded. These values are transformed into a word vector count presentation, where each row contains the token, sentiment category, and occurrence count. Consequently, the matrix count presentation serves as the foundation for measuring the tone of each report at the document level. The sentiment tone for each document is computed at the document level by aggregating frequency counts per sentiment class and calculating the shares of positivity, negativity, and uncertainty, as well as the overall sentiment. As illustrated in Chapter 2, the overall sentiment score (*Tone*) for each text is computed as the difference between the positive and negative frequencies, normalized by the total word count. The stop word category is excluded from the aggregated sentiment share and Tone because these words do not contribute to the sentiment.

4.5.2 Sentiment Analysis for English Financial Text

A parallel implementation is adapted for the English textual dataset using the same classification framework applied for Arabic, with several modifications to accommodate the differences between Arabic and English. The research utilizes the LM dictionary, namely the positive, negative, and uncertain word lists, to identify and classify the sentiment in annual reports and CEO letters. Importantly, unlike Arabic, English sentiment classification does not require lemmatization or further normalization because sentiment matching is applied to the original words as they appear in the text. This is made available because the LM dictionary includes word inflections. In addition, all sentiment lists in the LM dictionary are expressed in unigrams, eliminating the need to account for bigram and trigram matching. Nevertheless, the same rule-based function is utilized, using only unigram matching.

Similar to the classification framework applied for Arabic, the study employed negation forms proposed by Loughran and McDonald (2011), including *no*, *not*, *non*, *neither*, *never*, and *nobody*. The research applied the negation effect to negative and positive sentiment words within a three-word negation window. Additionally, the study employed the sentiment frequency matrix proposed for Arabic textual data to transform English textual data into a word-vector count representation. These numeric values are used to compute and generate sentiment classification categories, the share of sentiment words, and the overall sentiment at the document level using the same formula applied to the Arabic dataset. The combined classification methodology across Arabic and English, while accounting for their linguistic differences and dictionary structures, enables consistent sentiment comparison across the Arabic and English versions of the financial text and further serves as a baseline for downstream sentiment analysis.

4.6 Baseline Sentiment Analysis of Arabic and English Financial Text

Initially, this research applies the ArFinSD developed in this study to address the scarcity of finance-oriented Arabic dictionaries, thereby assessing its ability to measure tone in Arabic financial narratives. To meet the research aims and objectives, I conducted a comparative cross-language analysis utilizing the Arabic annual reports, CEO letters, and their English counterparts. The comparative analysis utilizes the ArFinSD and LM dictionary for Arabic and English, respectively (the word lists for both dictionaries are provided in Table 3.1, Chapter 3). The analysis provides insight into how sentiment is expressed and whether the tone is consistent across original financial disclosures in their respective language. Furthermore, in addition to assessing the ArFinSD's ability relative to the LM dictionary in terms of measuring tone in Arabic financial narratives, the current analysis serves as a baseline for sentiment classifications in downstream comparative analysis settings within the research.

Accordingly, the cross-language sentiment analysis applies the pre-processing pipelines and sentiment classification methodology outlined in Section 4.4 to Arabic financial disclosures and their English counterparts. In the baseline analysis, the research utilized annual reports and CEO letters obtained from the Tadawul website, as described in Section 4.2 and summarized in Table 4.1 and Table 4.2. For the Arabic financial text, the pre-processing steps include normalization, lemmatization, and custom stop word removal. Additionally, the preceding sections detail the dictionary-based implementation approach for Arabic, including n-gram modeling, negation detection, and the sentiment frequency matrix. Likewise, the preceding sections provide details of the pre-processing steps for the English documents, including normalization using the NLTK library and the custom stop word removal applied to the English dataset. Furthermore, a similar dictionary-based implementation approach is adopted for the English documents with only the unigram function applied. Both pre-processing pipelines ultimately prepared the text for dictionary-based sentiment classification, tailored to the linguistic aspect of each language.

4.7 Arabic Sentiment in General and Financial Dictionaries

A key motivation behind establishing a finance-oriented sentiment dictionary is the concept of polysemy, where a word's meaning varies depending on the context. To assess whether the proposed ArFinSD yields more accurate results than general dictionaries in financial settings, the research conducts a comparative textual sentiment analysis. The study employed one of the most comprehensive and widely available Arabic general dictionaries, the large-scale ArSenL (Badaro et al., 2014). The ArSenL has been employed in various Arabic sentiment analysis projects due to its broad lexical coverage and availability to the research community. The ArSenL is constructed using a combination of SWN, AWN, and the SAMA analyzer. The lexicon consists of 157k synsets and more than 28,000 lemma terms (Badaro et al., 2014). In addition, ArSenL's primary focus is MSA, the formal style of written communication used in official financial settings.

4.7.1 Setup of the Comparative Analysis

To conduct the comparative sentiment analysis, several procedures are implemented to prepare the ArSenL for application in financial textual analysis. The ArSenL dictionary provides lemma entries based on the Buckwalter transliteration scheme[27]. The Buckwalter Arabic schema is a widely used representation of Arabic characters in Latin script. The transliteration schema is utilized in various computational linguistics tasks because it provides a standardized representation of Arabic text, thereby making it easier to process in environments with limited support for the Arabic script. Nonetheless, it poses challenges for direct adaptation to Arabic financial texts and for sentiment classification. To address this issue, the research utilizes the CAMeL Tool to convert the Buckwalter-transliterated lemmas into Arabic-readable entries. This conversion ensures alignment between ArSenL's entries and those in ArFinSD. More importantly, transforming ArSenL's entries into lemma representations is essential for A dictionary-based analysis because the corpus is a collection of Arabic lemma entries.

In addition, ArSenL includes duplicate entries for some of the lemmas due to the authors' merge-based approach, where the English glosses or WordNet systems can provide a distinct sentiment score for the same Arabic lemma. Kaity and Balakrishnan (2020) highlighted several drawbacks associated with relying on multiple resources to construct a sentiment lexicon. Because the authors of the ArSenL relied on the ESWN synsets, which contain

[27] http://www.qamus.org/transliteration.htm

different senses of a given word, the lemmas result in duplicate entries in their dictionary, each with a different sentiment score. While this method addresses the word usage by accounting for different meanings across a word's synsets, it introduces ambiguity when determining a word's polarity in sentiment analysis tasks.

To address duplicate lemma entries, the research employs an averaging approach to create a unique-lemma dictionary version of the ArSenL following the authors' approach (Badaro et al., 2014). This involves combining duplicate lemma entries by averaging their sentiment scores, resulting in a standardized dictionary suitable for financial text analysis. This step is necessary to ensure that each lemma is represented by a single set of sentiment values, making the lexicon more suitable and less ambiguous for sentiment analysis in financial settings. During their sentiment analysis evaluation, the authors of ArSenL applied the average score approach when a lemma appeared multiple times (Badaro et al., 2014). They relied on aggregated positivity and negativity scores for each lemma that occurred numerous times in the lexicon, calculating the average across duplicates to obtain a distinct sentiment value for each lemma during analysis. This approach is well-established in the NLP literature and has been applied in previous sentiment analysis studies (see Guerini et al., 2013).

Additionally, the ArSenL is a score-based dictionary, whereby each lemma is assigned three sentiment scores reflecting positivity, negativity, and objectivity with a sum of 1. In contrast, the ArFinSD follows a category sentiment classification model similar to the LM dictionary. Averaging sentiment scores can resolve the problem of duplicate lemma entries in ArSenL but the dictionary continues to assign both positive and negative scores to each entry. A score-based schema is mainly used to determine the strength of sentiment (e.g., beautiful, pretty, gorgeous). This is useful in sentiment analysis application models that account for the intensity of sentiment beyond binary classification. Additionally, the scoring-based dictionary can be utilized in continuous-sentiment classification models where positivity and negativity scores are aggregated at the classification level (e.g., sentence or document). However, the ArFinSD follows a traditional binary classification approach, assigning each lemma to a sentiment class (e.g., positive, negative, or uncertain) without using numerical scoring.

The research aims to assess sentiment polarity in Arabic financial text using a binary dictionary and the dictionary-based sentiment analysis approach. Finance-oriented dictionaries, such as those of Henry (2008) and Loughran and McDonald (2011), use categorical structures to measure tone in financial settings. These resources are designed to capture the direction of sentiment rather than its degree, given that financial disclosures are carefully crafted to convey the firm's perspective on its performance and prospects. The ArFinSD is established according to this categorical structure to reflect the unique linguistic features of Arabic financial text. In contrast, ArSenL provides continuous scores for positivity, negativity, and objectivity, which can be more practical for general-purpose sentiment analysis than domain-specific dictionaries designed to measure tone in a particular setting.

The research applied a dominant-polarity decision rule to transform ArSenL's score-based entries into a binary sentiment structure equivalent to that of ArFinSD. This approach has been used in prior studies, such as those by El-Halees and Salah (2018), who applied the dominant polarity rule to convert ArSenL's scoring-based schema into a categorical structure dictionary. Under the dominant polarity rule, for each lemma m, the associated positivity and negativity scores, Pos(m) and Neg(m), were computed. The lemma is classified as positive if the positivity score exceeds the negativity score. If the negativity score exceeds the positivity score, it is assigned as a negative word. In cases where the two computed scores are equal or both zero, the lemma is categorized as neutral. The approach assumes that the direction of sentiment distribution reflects each lemma's sentiment class. The conversion can be formally illustrated as follows:

$$Dominant\ Polarity(m) = \begin{cases} positive, if Pos(m) > Neg(m) \\ Negative, if Neg(m) > Pos(m) \\ Neutral, if Pos(m) = Neg(m) \end{cases}$$

Converting a score-based dictionary into a categorical structure dictionary is a common approach in the NLP literature. Recalling that the ArSenL dictionary utilizes the ESWN to map the sentiment scores of the Arabic lemmas, it is important to note that the ESWN employs an identical scoring schema to that in the ArSenL dictionary (positivity, negativity, and objectivity, whose sum is equal to 1). Previous researchers have used the ESWN for sentiment analysis, transforming the dictionary from a scoring-based schema into a categorical sentiment resource (Ojeda-Hernández et al., 2023; Guerini et al., 2013). In these studies, the researchers proposed various strategies to conduct the conversion. For example, Ojeda-Hernández et al. (2023) employed normalization-based scoring to transform the dictionary into a binary classification category in which the polarity of the word is inferred from the normalized score sign:

$$s(m) = \frac{Pos(m)\ -\ Neg(m)}{Pos(m)\ +\ Neg(m)}$$

When comparing the dominant polarity rule with the normalized scoring approach of Ojeda-Hernández et al. (2023), we achieve 98.5% agreement between the two approaches across the ArSenL's lemma entries. The high level of consistency between the two conversion approaches confirms that the dominant rule decision yields accurate results in transforming the ArSenL lemma indices into a binary classification structure. After completing the preparation steps, including transliteration conversion, averaging duplicate-lemma scores, and restructuring the categorical polarity, the ArSenL was adapted to a format directly comparable to the ArFinSD. This alignment enables a systematic comparison between two sentiment dictionaries in terms of coverage, word overlap, and accuracy in financial applications.

Table 4.4 presents the total number of sentiment words across the two dictionaries as lemma entries. While ArSenL covers a broad range of sentiment entries due to its construction approach as a general-purpose lexicon, the ArFinSD reflects domain-specific words established for the Arabic finance narrative setting. The ArSenL was reported by Badaro et al. (2014) to contain 28,780 lemma entries, based on their manual correction version. The version used in the current analysis comprises 27,496 lemma entries, based on the official ArSenL package and its documentation, which were downloaded from the project's website[28] in March 2022. At the time of accessing the ArSenL, the authors did not provide updated notes to clarify the difference between the figures reported in their study (Badaro et al., 2014) and those observed in the official ArSenL package. The version employed in the research is 4.5% lower than the version reported in the original study, potentially due to subsequent updates made by the authors.

[28] The ArSenL 1.0 official documentation, including the sentiment lexicon and license agreement, was downloaded from their project's official website (http://oma-project.com) in March 2022. However, the website is no longer active as of May 2025.

Table 4.4 Number of Words in Sentiment Dictionaries

	Dimensionality	ArFinSD	ArSenL
Negative List			
	One-dimension	1,105	8,620
	Two-dimension	756	
	Three-dimension	260	
Positive List			
	One-dimension	355	7,753
	Two-dimension	197	
	Three-dimension	13	
Uncertainty List			
	One-dimension	182	-
	Two-dimension	170	-
	Three-dimension	66	-
Neutral list			
	One-dimension	-	11,123
	Total in dictionary	3,104	27,496

The table illustrates the number of words that appeared in the ArFinSD and ArSenL. The ArFinSD contains sentiment entries across three categories, including positive, negative, and uncertain. In addition, each category is based on dimensionality entries (e.g., أَسْهَل, اِكْتِشاف هامّ, and فَرِيد مِن نَوْع). In contrast, ArSenL contains three categories (negative, positive, and neutral) based only on unigram entries.

4.7.2 Pre-Processing Steps and Sentiment Analysis

To carry out the sentiment classification analysis, the research applies a dictionary-based sentiment approach using the ArFinSD and the general-purpose ArSenL lexicon. The underlying corpus comprises Arabic annual reports and CEO letters obtained from the Tadawul website, as outlined in Section 4.2 and summarized in Table 4.1 and Table 4.2. The pre-processing pipeline steps, including normalization, lemmatization, and stop word removal, are documented in Section 4.4.2. The implementation of sentiment classification for Arabic text is provided in Section 4.5.1.

The research modifies the stop word list used in sentiment classification when employing the general-purpose dictionary (ArSenL). Because the stop word lists introduced in Section 4.4.2 were adapted to fit the Arabic financial domain, several stop word entries overlap with sentiment words in ArSenL. This is a common phenomenon because stop word lists are task-specific; what is considered a stop word in one domain may be classified as a sentiment word in another. For example, Loughran and McDonald (2015) noted that words such as '*not*' and '*no*' in the diction pessimism words account for 45% of all the pessimistic words found in their sample of 10-K reports. However, these words are considered to be stop words in financial applications and do not convey a negative tone. To address the stop word overlap with ArSenL, the research prioritizes sentiment words and excludes them from the stop word list filtering. For example, stop words such as سَنَوِيّ (yearly), صِفْر (the second month of the Islamic calendar), عالَمِيّ (international), مَلَك (king), and أَمارَة (state) are sentiment words in ArSenL and, therefore, they are retained in the respective predefined wordlist in the sentiment analysis. However, because the research accounts for the negation effect on the sentiment classification, the Arabic negation forms (لا-Laa, ليس-Laysa, لن-Lan, لم-Lam, بلا-Bla, دون-Dwn, غير-Gyr, عدم-Edm, عكس-Eks) were prioritized. These forms were retained and processed using the rule-based negation algorithm. The algorithm identifies the form and scope of negation and reverses the polarity of the sentiment, as detailed in Section 4.5.1.

4.8 The Impact of Translation on Sentiment in Financial Disclosures

To investigate the impact of translation on sentiment analysis in financial disclosures, the research employs a comprehensive bidirectional experimental framework. The experiment setup consists of the following steps: (a) conducting sentiment analysis on the original Arabic financial disclosures; (b) automatically translating the original English financial reports into the Arabic language using a MT system; (c) conducting sentiment analysis on the translated English financial reports (now in Arabic); (d) evaluating the extent of sentiment loss between the original Arabic financial disclosures and their English-to-Arabic counterparts. Furthermore, these steps are complemented by evaluating the impact on the translation reverse direction to reveal any translation direction effect by: (e) conducting sentiment analysis on the original English financial disclosures; (f) automatically translating the original Arabic financial reports into English; (g) conducting sentiment analysis on the translated Arabic financial reports (now in English); and (h) evaluating the extent of sentiment loss between the original English financial disclosures and their Arabic-to-English counterparts. Incorporating both translation directions enables the assessment of direction-specific translation effects and the identification of asymmetrical patterns in sentiment in either direction.

4.8.1 Source Corpus and Machine Translation Process

To analyze the effect of translation on sentiment, the annual reports and CEO letters were subjected to automated MT in both directions: Arabic-to-English and English-to-Arabic. At this stage, the research relies on the initial extracted plain text versions of annual reports and CEO letters, as discussed in Section 4.3.1. These original Arabic and English plain texts constitute the baseline corpora used in the MT. Appendix B.1 (a-1) offers a statistical summary of the initial extracted text for both languages utilized in the MT system. To establish the machine-translated versions, the research employs the Machine Translate API which leverages advanced NMT technology known for its high performance across a wide range of languages. Each annual report and CEO letter was translated in its entirety to preserve contextual coherence and maintain structural similarity to the baseline corpora.

Furthermore, the research uses the Google Cloud Translation Basic Model (v2)[29] for translation. The cloud service API was programmatically accessible via a Python pipeline, with secure access via a unique API key. Additionally, translation was carried out in batches via the cloud-based Google Translate API due to the source character limit of 100,000 bytes per request. To comply with the API character limits and preserve the narrative structure, each document was partitioned into contiguous segments at sentence boundaries, with a maximum partition size of 36,000 bytes per request. The research employed a custom function that identifies sentence boundaries at full stop characters, thereby avoiding mid-sentence splits and maintaining semantic and contextual order throughout the translation process. To reduce the risk of exceeding API rate limits, a one-second pause was added between each translation batch request, ensuring that the request rate remained well within the service limits and avoiding rate limit errors. The text partitions were translated sequentially in batches of up to ten segments per API request. Upon completion of each batch, the translated segments were reassembled in their original order, resulting in the final translated versions of the annual reports and CEO letters. A further manual check was conducted on the newly translated documents in both languages before the pre-processing and sentiment analysis phase.

4.8.2 Description of Machine-Translated Financial Textual Data

This section summarizes the size and composition of the translated versions of the annual reports and CEO letters analyzed in this research. After the translation process, four additional corpora were established for the annual reports and CEO letters: the Arabic-to-English corpus (hereafter, the translated English reports or letters) and the English-to-Arabic corpus (hereafter, the translated Arabic reports or letters). Tables 4.5 and 4.6 provide an overview of the number of documents and word counts for each corpus. These summaries reflect the final textual datasets suitable for sentiment analysis after establishing word definitions for each language and applying pre-processing and stop-word removal to the translated Arabic and English annual

[29] For more details, visit: https://cloud.google.com/translate/docs/editions

reports and CEO letters. Therefore, the translated Arabic and English financial texts described in Table 4.5 and Table 4.6 lay the foundation for the subsequent sentiment analysis and translation impact assessment. The initial bidirectional MT results for Arabic and English annual reports and CEO letters are provided in Appendix B.1 (b-1).

Table 4.5 Summary Statistics of the Machine-Translated Annual Reports

	Reports	Total word count	Words per document				
			Mean	Median	SD	Min	Max
Translated Arabic reports	728	5,738,096	7,882	6,205	5,795	451	41,106
Translated English reports	728	5,204,472	7,149	5,537	5,281	381	35,859

This table presents summary statistics for 728 machine-translated annual reports available in both Arabic and English. In Arabic, a word is defined as a sequence of at least two characters, whereas in English, a word is defined as a sequence of at least three characters. The translated Arabic reports reflect the original English reports which were translated into Arabic using the Google Cloud Translation API. The translated English reports reflect the original Arabic reports which were translated into English using the Google Cloud Translation API. In addition, the summary statistics reflect the corpus size after applying the stop word removal and text cleaning pre-processing steps. The stop word lists employed in this research are detailed in Appendix B.4. For a comparison reference, summary statistics for the original Arabic and their English counterparts at the same stage are provided in Table 4.1.

Table 4.6 Summary Statistics of the Machine-Translated CEO Letters

	Letters	Total Words	Words per document				
			Mean	Median	SD	Min	Max
Translated Arabic letters	274	151,145	551	463	406	55	2,784
Translated English letters	274	136,632	498	409	350	90	2,037

This table presents summary statistics for 274 machine-translated CEO letters available in both Arabic and English. In Arabic, a word is defined as a sequence of at least two characters, whereas in English, a word is defined as a sequence of at least three characters. The translated Arabic reports reflect the original English reports which were translated into Arabic using the Google Cloud Translation API. The translated English reports reflect the original Arabic reports which were translated into English using the Google Cloud Translation API. In addition, the summary statistics reflect the corpus size after applying the stop word removal and text cleaning pre-processing steps. The stop word lists employed in this research are detailed in Appendix B.4. For reference, summary statistics for the original Arabic and their English counterparts at the same stage are provided in Table 4.2.

4.8.3 Pre-Processing Steps and Sentiment Analysis

The sentiment analysis in the translation impact experiment follows the dictionary-based approach and implementation established in the baseline analysis of the original financial disclosures in their respective languages (see Section 4.6). The current sentiment analysis mirrors the methodological and pre-processing steps followed in the baseline sentiment analysis which utilized the original versions of the annual reports and CEO letters. To briefly describe the sentiment analysis approach, the research classifies sentiment by matching each report's content against two finance-oriented dictionaries: the ArFinSD for the Arabic version and the LM dictionary for the English version (the word lists for both dictionaries are provided in Chapter 3, Table 3.1). In addition, the research applies the same pre-processing steps outlined in Sections 4.4.2 and 4.4.3 to the translated financial documents, including both Arabic and English versions. For both languages, pre-processing steps start with normalization to standardize text encoding and resolve inconsistencies in character representation. The Arabic versions of the annual reports and CEO letters underwent the same pre-processing sequence but were further lemmatized using the CAMeL tool's disambiguation analyzer (MLE), as described in Section 4.4.2. These pre-processing workflows align with the steps applied to the original versions of the dataset, which is necessary to assess the translation impact of these versions. Finally, the research applies the dictionary-based approach framework described in Section 4.5, following the classification of n-gram modeling for Arabic and negation handling in both languages. This is conducted by relying on the custom sentiment classification function established for the research framework and sentiment identification. The consistent application of the methodology enables a valid cross-language comparison of sentiment shifts between the original and translated documents, leading to a more accurate interpretation of the sentiment shifts resulting from the MT process.

4.9 Methodological Limitations

Several drawbacks are associated with the NLP tools employed, the characteristics of the textual data, and the pre-processing strategies applied to Arabic and English textual data. The research relies on CAMeL's library to perform disambiguation using its MLE model. This step involves converting the Arabic text from original words to lemmatized words, a key foundation of the dictionary-based approach, and then comparing these words against predefined sentiment word lists in the ArFinSD. While CAMeL Library is considered one of the most comprehensive and advanced Arabic NLP tools available to the research community, it may fall short in terms of accurately disambiguating certain words. Lemmatization tools, including CAMeL's MLE, are based on training corpora or grammatical rules schemes which may generate incorrect lemmas or fail to analyze rare, compound, or domain-specific terms. Therefore, the sentiment classification results may be affected to a minor degree.

Although the disambiguator occasionally fails to accurately provide the lemma form or offers an incorrect analysis, such instances are limited in the research's analysis. This is because the textual narratives in the annual reports and CEO letters are expressed in MSA, the official form of communication. This type of communication is grammatically structured and carefully crafted, unlike Arabic dialects which can be noisy (e.g., spelling mistakes, repeated letters) and include regional words that NLP systems may fail to recognize. Arabic financial disclosures are considered less challenging for Arabic NLP tools because these models are inherently trained on MSA corpora.

The current research adopted two strategies to mitigate the issue. First, the annual reports and CEO letters were processed as complete text and the sentence structures were incorporated into the model as they appear in the documents. This is important because the CAMeL model expects the text to be sentences rather than individual words. Second, a sample of lemma outputs was manually reviewed and cross-checked against the BERT-based CAMeL disambiguator. The research further conducted a mirror analysis using the BERT-based model on the corpus and concluded that the results were almost identical (see Appendix B.2 for further details).

Another limitation may stem from the comparison of sentiment analysis between the original Arabic (using ArFinSD) and the original English (using the LM dictionary) annual reports and CEO letters, which should be interpreted with caution. Although both pipelines follow the same dictionary-based approach, the pre-processing steps differ in several aspects. The Arabic textual data were lemmatized to reduce morphological variation (see Table 4.3 for details), whereas the English versions were processed in their original inflected forms. Furthermore, the negation detection model is expected to behave differently across the two languages due to differences in negation expression (implicit versus explicit forms) between Arabic and English.

Likewise, the Arabic language sentiment analysis classification was extended to n-gram modeling, including up to three-word combinations. However, in the English sentiment analysis, the LM dictionary was primarily applied at the unigram level. It is worthy of note that a key motivation for adapting n-gram modeling for Arabic is that an extensive collection of negative words in the LM can only be translated into multi-word Arabic equivalents. In response to this phenomenon, the research adopts multi-word expressions via n-gram modeling because negative sentiment in financial disclosures is more tone-revealing and associated with market-linked reactions (Henry & Leone, 2016; Loughran & McDonald, 2011). As a result, differences in sentiment words may lead to variations in coverage across the languages, despite both documents relying on finance-oriented dictionaries for sentiment classification.

Lastly, the research assumes that the Arabic and English versions of the annual report represent direct counterparts because both are formally established and published by the same firms. However, the process by which companies construct their bilingual reports remains ambiguous. It is unclear whether these financial reports are produced through direct translation or written independently to address different potential audiences. The equivalence assumption underlies the MT analysis experiment which compares original and translated versions of annual reports using a normalized sentiment dictionary. While this assumption provides a necessary foundation for the cross-language sentiment comparison, it may introduce uncertainty regarding the communicative strategy behind each version.

4.10 Concluding Remarks

The chapter thoroughly detailed the comprehensive process undertaken to develop and prepare the Arabic and English financial disclosures used in this research for the dictionary sentiment analysis. It began by providing a descriptive summary of the Arabic and English annual reports and CEO letters, aligned with the extraction method, scope, and challenges encountered during the extraction process to maintain alignment between the bilingual versions.

The chapter also described the design and implementation of pre-processing pipelines that prepared the data for sentiment analysis. To overcome the morphological complexity of Arabic, the chapter documents the NLP techniques integrated, including normalization, lemmatization, and stop word removal. The chapter provided an in-depth discussion of resource selection, including morphological disambiguation and the CAMeL library, supported by comprehensive literature validation. The English financial reports were processed using the NLTK library, requiring fewer preprocessing steps. Next, the chapter described the dictionary-based sentiment analysis implementation for both languages, highlighting negation detection and the adoption of n-gram modeling for Arabic textual data.

Furthermore, the chapter documented three proposed sentiment analysis frameworks: baseline cross-language sentiment analysis, competitive analysis across ArFinSD and ArSenL, and translation impact assessment via sentiment analysis. The first analysis uses the companies' original financial disclosures and measures sentiment using the ArFinSD and the LM dictionary. The second comparison analysis framework and pre-processing steps were presented to evaluate how well the ArFinSD and ArSenL sentiment dictionaries capture the tone in financial texts. Subsequently, the chapter outlined the construction of the MT corpus, enabling the research to evaluate sentiment preservation across machine-translated documents. With the textual datasets and sentiment analysis frameworks thoroughly described and prepared, the next chapter builds upon these foundations to present sentiment classification results across Arabic and English financial disclosures, interpret them, and examine their implications.

Chapter 5. Textual Analysis Results and Discussion

5.1 Introduction

This chapter presents the results of the textual sentiment analysis conducted on Arabic and English financial disclosures, specifically the annual reports and CEO letters described in the preceding chapter. The primary objectives of this chapter are to present and discuss the results of the dictionary-based sentiment analysis methodology implemented and discussed in the previous chapters, evaluating the ArFinSD in a cross-language sentiment analysis setting. Building upon the corpus preparation, pre-processing pipelines, and sentiment classification procedures detailed in Chapter 4, this chapter applies the proposed frameworks to examine linguistic patterns, sentiment distribution, and alignment across languages.

The analysis is structured around three main comparative dimensions that correspond to the research's objectives. The first analysis assesses whether tone differs between Arabic and English versions of the financial disclosures, offering in-depth insight into the linguistic asymmetries in bilingual reporting settings. At the same time, the analysis provides evidence regarding whether the ArFinSD, developed in this research, is able to effectively measure the tone in Arabic financial narratives similar to the LM dictionary. The second analysis presented in this chapter reveals the comparative results concerning the use of Arabic finance-oriented and general-purpose dictionaries in Arabic financial text, along with their efficacy in accurately assessing tone in financial contexts. The third analysis is constructed to assert whether the financial disclosures exhibit sentiment consistency between the original and machine-translated versions.

Furthermore, the chapter provides insight into the role of negation in sentiment analysis across Arabic and English financial documents. It demonstrates negation detection and its impact on financial text in both languages, reflecting its role in accurately capturing tone in financial settings, and examines the linguistic differences in how negation is handled across Arabic and English.

The chapter is structured as follows. Section 5.2 presents an overview of the sentiment analysis conducted throughout the chapter. Section 5.3 presents the sentiment analysis results and a discussion of the Arabic and English original financial documents, evaluating the ability of ArFinSD to measure sentiment with respect to the LM dictionary. Section 5.4 provides insight into the negation role across the Arabic and English financial narratives. Section 5.5 investigates the shift in meaning between ArFinSD and the Arabic general sentiment dictionary, ArSenL, providing a comparative textual evaluation. Section 5.6 examines the effect of translation on sentiment preservation across Arabic and English financial texts. Section 5.7 discusses the limitations of the results across the proposed sentiment analysis settings, followed by Section 5.8, which concludes the chapter with final remarks.

5.2 Textual Sentiment Analysis Results Overview

This section presents the results of textual sentiment analysis for Arabic financial texts and their English counterparts. The Arabic sentiment analysis literature notably lacks a finance-oriented dictionary capable of gauging the tone in finance and business applications. To address this gap, the research proposed a new ArFinSD to measure tone in financial textual settings by adapting and translating the English LM dictionary. The primary objective is to determine whether the ArFinSD provides more accurate tone measurements in Arabic financial settings. In the current study, I applied dictionary-based sentiment analysis to annual reports and CEO letters in both languages to assess the proposed ArFinSD's performance, compare it with Arabic general dictionaries, and observe the impact of translation on sentiment.

The sentiment analysis results are structured in three main dimensions. First, comparative sentiment analysis is conducted using the annual reports and CEO letters. The research reports sentiment word-level frequency distributions based on predefined sentiment words across three categories (positive, negative, and uncertain) in both languages using the ArFinSD and LM dictionary. Additionally, the analysis examines the ArFinSD's capacity to capture sentiment in Arabic financial texts. It compares it to English financial texts, as measured by the LM dictionary, highlighting the linguistic asymmetry between the two languages. Moreover, the research further examines the sentiment classification agreement between the ArFinSD and the LM dictionary based on the agreement assessment methodology outlined in Chapter 3, Section 3.6. The sentiment classification implementation of the dictionary-based approach follows and leverages the custom rule-based matching classifier illustrated in Chapter 4, Section 4.5 to perform the analysis and produce a sentiment frequency distribution in both languages. The research refers to the first analysis presented in the following section as the baseline analysis that is further employed to assess the Arabic and English textual sentiment in the proposed sentiment analysis settings.

Second, the study evaluates the proposed ArFinSD against the general Arabic dictionary, ArSenL, to evaluate its ability to measure the tone in finance-domain settings. The finance and accounting literature provide extensive evidence that finance-oriented sentiment dictionaries outperform general sentiment dictionaries in terms of accurately measuring tone in financial settings, where general dictionaries often misclassify sentiment and fail to accurately capture tone. Building upon this foundation, the research extends the literature to the Arabic language and examines whether similar limitations exist in Arabic financial settings. Third, the research examines the impact of MT on sentiment across both languages, focusing on the tone expressed in annual reports and CEO letters. While the NLP literature has investigated the topic of 'sentiment lost in translation,' little is known about the impact of translation on financial disclosures, especially in the Arabic-English context.

5.3 Baseline Sentiment Analysis of Financial Text: Arabic and English

Building upon the methodological implementation established in Sections 4.4 and 4.5, and the baseline analysis design in Section 4.6 of the previous chapter, the research applies a dictionary-based sentiment analysis approach to the Arabic and their corresponding English annual reports and CEO letters to evaluate the degree of tone expressed within these documents. Table 5.1 presents the most frequent positive, negative, and uncertain words in the Arabic and English annual reports. Sentiment words are classified using the ArFinSD and LM dictionaries. Arabic sentiment words were classified using lemma-level matching, including unigrams, bigrams, and trigrams. In contrast, English sentiment words were classified using the LM dictionary, which primarily includes only unigram entries and inflected forms.

According to Panel A in Table 5.1, the total number of positive sentiment words identified in Arabic annual reports is 282,927, whereas the corresponding number of positive words in English annual reports is 117,137. Likewise, Panel B in Table 5.1 presents the most frequently occurring negative words in the annual reports for both languages. The number of negative sentiment words identified in the Arabic annual reports (139,645) is significantly higher than in their corresponding English reports (80,869). Additionally, Panel C of the table presents the most frequently occurring uncertain sentiment words in the Arabic and English annual reports. The number of uncertain words identified in the Arabic (104,580) and English (86,033) documents is relatively close compared to the other two sentiment categories. The Arabic and English versions of the annual reports indicated a higher degree of positivity than the other sentiment categories. This remains true despite the fact that the positive sentiment categories in the ArFinSD and LM dictionaries are smaller in number compared to the negative lists, with 565 versus 2,121 entries in the ArFinSD, and 347 versus 2,345 entries in the LM dictionary.

Table 5.1 Most Frequent Sentiment Words in Arabic and English Annual Reports*

Rank	ArFinSD				LM Dictionary			
	Word	Total	%	Cum %	Word	Total	%	Cum %
Panel A: Most common positive words								
1	تَحْقِيق	16,828	5.86	5.86	achieve	5,493	4.68	4.68
2	تَطْوِير	15,819	5.51	11.36	best	5,004	4.26	8.93
3	نُمُوّ	11,890	4.14	15.50	efficiency	4,216	3.59	12.52
4	تَعْزِيز	11,499	4.00	19.51	opportunities	3,920	3.34	15.86
5	دَعْم	9,777	3.40	22.91	enhance	3,403	2.90	18.76
6	قُدْرَة	9,434	3.28	26.19	strong	3,274	2.79	21.54
7	تَحْسِين	8,875	3.09	29.28	achieving	3,122	2.66	24.20
8	ضَمان	8,431	2.93	32.22	improve	3,108	2.65	26.85
9	كَفاءَة	7,015	2.44	34.66	leading	3,008	2.56	29.41
10	أَعْلَى	6,627	2.31	36.97	achieved	2,874	2.45	31.85
All		282,927				117,137		
Panel B: Most common negative words								
1	خَسارَة	7,431	5.86	5.86	loss	4,145	5.22	5.22
2	اِنْخِفاض	5,079	4.01	9.87	losses	2,835	3.57	8.80
3	تَحَدِّي	3,407	2.69	12.55	against	2,550	3.21	12.01
4	تَعْوِيض	2,904	2.29	14.84	challenges	2,447	3.08	15.09
5	تَقْلِيل	2,744	2.16	17.01	claims	1,890	2.38	17.48
6	خَضَع	2,037	1.61	18.62	conflict	1,499	1.89	19.36
7	سَلْبِيّ	1,983	1.56	20.18	impairment	1,485	1.87	21.24
8	تَخْفِيض	1,686	1.33	21.51	exposed	1,469	1.85	23.09
9	عارَض	1,655	1.31	22.81	negative	1,123	1.42	24.50
10	مُواجَهَة	1,545	1.22	24.03	weaknesses	975	1.23	25.73
All		139,645				80,869		
Panel C: Most common uncertain words								
1	مَخاطِر	44,938	51.97	51.97	risk	27,995	33.66	33.66
2	مُتَوَقَّع	4,586	5.30	57.28	risks	17,901	21.52	55.18
3	مُقْتَرَح	2,995	3.46	60.74	may	13,655	16.42	71.60
4	تَعَرَّض	2,684	3.10	63.84	could	2,015	2.42	74.02
5	مُحْتَمَل	2,677	3.10	66.94	possible	1,887	2.27	76.29
6	تَوَقَّع	2,662	3.08	70.02	exposure	1,807	2.17	78.46
7	قَدَّر	2,353	2.72	72.74	approximately	926	1.11	79.57
8	مُتَغَيِّر	1,749	2.02	74.76	believes	918	1.10	80.68
9	مَعْقُول	1,579	1.83	76.59	precautionary	867	1.04	81.72
10	إِيضاح	1,406	1.63	78.21	fluctuations	851	1.02	82.74
All		104,580				86,033		

This table presents the most frequent positive, negative, and uncertain sentiment words in Arabic annual reports, along with their corresponding English equivalents. The occurrences of English words were classified using the LM dictionary, whereas the Arabic words were identified using the ArFinSD. The English words were extracted based on their surface forms, whereas the Arabic words were extracted based on the lemmatized forms. Arabic word frequencies and cumulative percentages reflect lemma/token-level matches. As a result, the words 'risk' and 'risks' correspond to the word (مَخاطِر) in Arabic. Also, some Arabic words can correspond to multiple English translation equivalents. For example, the word (تَحْقِيق) is translated to 'achieve,' 'accomplish,' and 'attain.' An extended list of the most frequent sentiment words is provided in Appendix C.1 for Arabic and Appendix C.2 for English. * Table designs are inspired by the work of Bannier et al. (2019) and Loughran and McDonald (2011, 2015)

The ten most common positive words across the two versions of the annual reports show lexical overlap. The most frequently occurring Arabic positive word recorded in the annual reports is تَحْقِيق (achieving), with 15,828 occurrences (5.86% of the total number of positive words). In English, the words *advancing* (200; 0.17%), *enhancement* (359; 0.31%), *enhancing* (1,980; 1.68%), *improvement* (1,641; 1.39%), and *improving* (2,062; 1.75%) correspond to the word تَطْوِير, the second-highest ranked positive word in the Arabic annual report (5.51% of the total number of positive words). These English translations, corresponding to تَطْوِير, address the Arabic word as a noun. However, the English translations are not exclusive to the Arabic word تَطْوِير because they may represent other positive Arabic words in the ArFinSD. For example, the English word *enhancement* corresponds to the Arabic words تَعْزِيز (11,499; 4%) and تَحْسِين (8,875; 3.08%) which rank fourth and seventh, respectively, among the most frequent positive Arabic words identified in the annual reports. Section 5.3.1 provides further details of lexical translation overlap across the ArFinSD and LM dictionary.

In the negative category, the word خَسارَة (7,431; 5.86%) and its corresponding English inflected forms, *loss* (4,145; 5.22%) and *losses* (2,835; 3.57%), remain among the most frequent identified negative words across the Arabic and English annual reports. Similarly, the word *challenges* ranked fourth with 2,447 occurrences, accounting for 3.08% of the total negative words identified in the English annual reports corpus. Consequently, the Arabic word تَحَدِّي, recorded 3,407 times, accounted for 2.69% of the total negative words identified, but the Arabic word تَحَدِّي also corresponds to the English inflected form recorded within the English annual reports, including *challenging* (584), *challenge* (392), and *challenged* (39). Collectively, the top-most common negative words across the two versions account for 24.03% in Arabic annual reports and 25.73% in their English counterparts.

The word-level identification of the uncertainty category also shows a similar trend across the two versions of the annual reports. The most common uncertain word is مَخاطِر, with its English corresponding equivalents *risk* and *risks*, which together account for more than 50% of the recorded uncertain words. This is similar to what was reported by Bannier et al. (2019) who found that the words *risk* and *risks* accounted for 41.9% of all uncertain categories in the English versions of annual reports. The words *possible* (1,887; 2.27%) and مُحْتَمَل (2,677; 3.10%) both ranked fifth in their respective version of the annual report and sentiment dictionaries, and they correspond exclusively to each other. Collectively, the ten most common uncertain words across the two versions account for 78.21% in Arabic annual reports and 82.74% in their English counterparts, indicating their significance within the category of uncertainty in the ArFinSD and LM dictionaries.

Furthermore, in the Arabic annual reports, multidimensional sentiment words accounted for a share of the total number of sentiment words identified. The sentiment analysis revealed that in the positivity category, 7,483 two-dimensional words and 386 three-dimensional words were identified. رَغْم مِن (despite), عَلَى رَغْم (despite), شَكْل كَبِير (greatly), شَكْل مُسْتَمِرّ (diligently), and شَكْل فَعّال (efficiently) were among the most frequent positive two-dimensional words recorded in the Arabic annual reports. Among the three-dimensional words most commonly identified in the annual reports are إِلَى حَدّ كَبِير (greatly), فَرِيد مِن نَوْع (unsurpassed), and لا مَثِيل لِ (unmatched; unparalleled; unsurpassed), which together accounted for 98.97% of the three-dimensional words recorded. The positive multidimensional sentiment words account for approximately 2.79% of the total positive words identified in the Arabic annual report.

In the negativity multidimensional sentiment words category, 10,458 occurrences were identified for two-dimensional words and 465 occurrences for three-dimensional words. Two-dimensional words such as عَدَم قُدْرَة (inability; incapacity), إعادَة هَيْكَلَة (restructure), اِنْخِفاض قِيمَة (deprecation), and عَدَم اِلْتِزام (noncompliance) ranked as the most frequent words identified in Arabic annual reports, whereas تَخَلُّف عَن سَداد (arrearage), غَيْر مُصَرَّح بِ (unapproved; unauthorized), غَيْر قابِل إِلْغاء (indefeasible; indefeasibly), and غَيْر قابِل اِسْتِرْداد (irrecoverable; irrecoverably; nonrecoverable; unrecoverable) were the three-dimensional negative words most commonly identified in Arabic annual reports. Collectively, multidimensional negative sentiment words account for 7.82% of the total words recorded in the Arabic annual reports.

Additionally, there were 2,128 (2.03% of the total words) occurrences in uncertain multidimensional words identified in Arabic annual reports. For example, words such as مِن مُحْتَمَل (conceivably; probably), غَيْر مَلْمُوس (intangible), مُمْكِن أَنَّ (could), مِن حِين آخَر (sometime), إِلَى حَدّ ما (somewhat), and غَيْر قابِل مُلاحَظَة (unobservable) were among the most common uncertain multidimensional words appearing within the annual reports. Furthermore, because the ArFinSD allows for sentiment class sharing between the negative and uncertain categories, لا أَمْكَن تَنَبُّؤ (unforeseeable; unpredictability; unpredictable), غَيْر مُخَطَّط لِ (unforeseen; unintentional), and نَحْو غَيْر مُتَوَقَّع (unexpectedly) were the common negative and uncertain occurring multidimensional words recorded.

Table 5.2 Most Frequent Sentiment Words in Arabic and English CEO Letters

Rank	ArFinSD				LM Dictionary			
	Word	Total	%	Cum %	Word	Total	%	Cum %
Panel A: Most common positive words								
1	نُمُوّ	1,132	6.67	6.67	success	326	4.3	4.03
2	تَحْقِيق	1,094	6.44	13.11	opportunities	280	3.7	8.00
3	تَعْزِيز	761	4.48	17.59	achieved	263	3.47	11.47
4	تَطْوِير	725	4.27	21.86	strong	263	3.47	14.95
5	دَعْم	613	3.61	25.47	achieve	249	3.29	18.23
6	نَجاح	493	2.90	28.38	best	249	3.29	21.52
7	حَقَّق	485	2.86	31.23	achieving	209	2.76	24.28
8	تَحْسِين	398	2.34	33.58	leading	203	2.68	26.96
9	إِنْجاز	384	2.26	35.84	innovation	201	2.65	29.61
10	فُرْصَة	384	2.26	38.10	achieved	2,874	2.45	31.85
All		16,882				7,556		
Panel B: Most common negative words								
1	تَحَدِّي	343	13.10	13.10	challenges	254	18.18	18.18
2	خَسارَة	103	3.93	17.04	loss	67	4.8	22.98
3	اِنْخِفاض	95	3.63	20.66	challenging	53	3.79	26.77
4	خَفْض	75	2.86	23.53	against	44	3.15	29.92
5	مُواجَهَة	74	2.83	26.36	overcome	42	3.01	32.93
6	تَقْلِيل	63	2.41	28.76	crisis	39	2.79	35.72
7	صَعْب	55	2.10	30.86	losses	36	2.58	38.03
8	تَداعِي	51	1.95	32.81	difficult	30	2.15	40.44
9	بالِغ	49	1.87	34.68	negative	25	1.79	42.23
10	أَزْمَة	46	1.76	36.44	claims	24	1.72	43.95
All		2,746				1,419		
Panel C: Most common uncertain words								
1	مَخاطِر	110	11.92	11.92	may	62	11.36	11.36
2	قَدَّر	77	8.34	20.26	risk	60	10.99	22.34
3	تَوَقَّع	74	8.02	28.28	possible	52	9.52	31.87
4	مُتَوَقَّع	71	7.69	35.97	believe	51	9.34	41.21
5	تَوَقَّع	66	7.15	43.12	risks	32	5.86	47.07
6	مُتَغَيِّر	66	7.15	50.27	approximately	30	5.49	52.56
7	أَظْهَر	63	6.83	57.10	could	25	4.58	57.14
8	إِمْكانِيَّة	63	6.83	63.92	almost	20	3.66	60.81
9	حِوال	36	3.90	67.82	anticipate	18	3.3	64.01
10	مُحْتَمَل	23	2.49	70.31	nearly	17	3.11	67.22
All		1,103				587		

This table presents the most frequent positive, negative, and uncertain sentiment words in Arabic CEO letters, along with their corresponding English equivalents. The occurrences of English words were computed using the LM dictionary, whereas the Arabic words were calculated using the ArFinSD. In English, inflected forms were used for sentiment classification. As a result, the words 'risk' and 'risks' correspond to the word (مَخاطِر), which is based on the ArFinSD lemma entry that reflects a variety of morphological forms of the same word. An extended list of the most frequent sentiment words is provided in Appendix C.3 for Arabic and Appendix C.4 for English.

Table 5.2 presents the most frequent sentiment words in Arabic CEO letters, along with their corresponding English equivalents, categorized as negative, positive, and uncertain. Unlike annual reports, CEO letters are conservatively short, with a median of 468 words in Arabic and 382 in English, as shown in Table 4.2. CEO letters are substantially different in terms of both linguistic style and content. The importance of CEO letters lies in their ability to convey valuable information beyond the scope of audited financial statements, including narrative explanations and interpretations that are not captured in formal financial statements (Abrahamson & Amir, 1996). CEO letters tend to be less technical and more narrative in nature than other sections of the annual report, which are heavily regulated by corporate governance standards, follow regulatory templates, and share a similar neutral tone. As a result, CEO letters are valuable for sentiment analysis because they may convey a managerial tone.

Similar to annual reports, Table 5.2 shows that positive sentiment words continue to be dominant in CEO letters, both in Arabic and their English counterparts. ArFinSD identifies 16,882 positive words compared to 7,556 in English using the ArFinSD and LM dictionaries, respectively. In Arabic CEO letters, the words نُمُوّ (progress), تَحْقِيق (achieving), تَعْزِيز (bolstering; boost; enhancing), تَطْوِير (improvement; improving; advancing; enhancement; enhancing), and دَعْم (strengthened; encouraged; encouragement) are among the most common positive words. In English, success (نَجاح), opportunities (فُرْصَة), achieved (أَنْجَز; حَقَّق; مُحْرِز; مُحَقَّق; أَحْرَز), strong (مَتِين; راسِخ; قَوِيّ), and achieve (أَنْجَز; حَقَّق; أَحْرَز) were the top five most used positive words in CEO letters. Arabic and English positive words identified in the CEO letters exhibit lexical similarity. The Arabic translation of positive English words corresponds to the highest-ranking English words, including *success*, *opportunities*, and *achieved*. For instance, the word *success* appeared 326 times (4.3% of the total positive words) and it corresponds to نَجاح with 493 occurrences. Because the English word *strong* corresponds to three Arabic equivalent translations, the words قَوِيّ ranked 19th with 245 occurrences, راسِخ ranked 50th with 74 occurrences, and مَتِين ranked 123rd with 18 occurrences.

Furthermore, the most commonly occurring negative word in Arabic CEO letters is تَحَدِّي, which appears 344 times. This lemma corresponds to the English word challenge and its inflected forms challenges (254 times), challenge (19 times), challenging (53 times), and challenged (2 times). Notably, all of these forms are classified as both nouns and verbs in English. Accordingly, the Arabic verb تَحَدَّى is a valid equivalent translation to the word challenge and its inflected forms. However, the verb تَحَدَّى appears only once in the CEO letters corpus. Lemma recognition indicates that the CAMeL disambiguator recognized the word challenge and all of its inflected forms as nouns in Arabic and assigned them under the noun form تَحَدِّي.

5.3.1 Sentiment Analysis Comparison: Arabic and English

The phenomenon of high-frequency sentiment words observed in Arabic annual reports and CEO letters stems from key linguistic differences between Arabic and English, as well as structural distinctions between the ArFinSD and LM dictionaries. At the word/lemma level, the ArFinSD identifies significantly higher match frequencies due to its lemma-based structure and Arabic's morphological richness. The lemmatization process enables the grouping of a range of Arabic inflected surface forms and structurally distinct forms of a given word under a single lemma, thereby merging all semantically equivalent variations. For instance, the word خَسارَة (loss) appears in the Arabic annual reports 7,431 times. Consequently, in English, the corresponding word *loss* appears 4,145 times, whereas its inflected forms *losses* and *losing* occur 4,145 and 73 times, respectively.

To that end, each Arabic sentiment word is not matched solely based on surface form but also on extended grammatical and linguistic features, including gender, number, case, person, mood, voice, and tense. The first four Arabic positive sentiment words (تَحْقِيق, تَطْوِير, تَعْزِيز, نُمُو) in the annual report are identified 56,036 times and account for almost 20% of all sentiment words within the positive sentiment category. Each of these high-frequency occurring words includes a broader range of different forms. For instance, the lemma تَعْزِيز (bolstering; boost; enhancing) includes various morphological forms such as تعزيز, وتعزيز, وتعزيزا, تعزيزها, وتعزيزه, لتعزيز, بتعزيز, and وتعزيزا. Consequently, all morphological forms are regrouped under their base lemma form to enable sentiment dictionary matching. In contrast, English textual analysis in the current study considers the word's original surface form as it appears in the text. For instance, the words *achieve*, *achieving*, *achieved*, and *achievements* are the most frequent positive sentiment words in English annual reports. The inflected forms of the word *achieve* account for 14% of the positive sentiment words. As a result, the total count of the English sentiment words is distributed across multiple inflected forms for the same lexical form.

Beyond surface word-level matching, Arabic lemma-based matching further inflates the frequencies of individual Arabic sentiment lemmas. The ArFinSD contains lemma forms categorized based on their part of speech, such as nouns, verbs, and adjectives. The lemma entries in the ArFinSD serve as matching units in the sentiment classification. Due to the rich morphological structure in the Arabic language, each lemma can generate more inflected forms. Crucially, the research relies on an Arabic MLE morphological disambiguator capable of identifying the appropriate interpretation of the words and mapping them to their lookup lemmas. Given Arabic's rich morphology and grammatical complexity, the disambiguator is more likely to capture broader inflection forms than in the English classification surface approach. Similarly, when the English annual reports are normalized using stemming, a similar pattern is observed. The study employs dictionary-based analysis on stemmed annual reports and the LM dictionary, as detailed in Appendix B.3. This resulted in an increase in detected positive words from 117,137 (surface inflected forms) to 179,108.

Furthermore, the English LM dictionary construction relies on a threshold and external lexical resources, such as the 2of12inf dictionary, to incorporate and validate inflected forms. As discussed in Chapter 3, Section 3.2.2, the authors set the inclusion threshold for inflected forms in the LM dictionaries at 50 occurrences, in addition to external variation. However, this approach excludes certain inflected forms that neither appear in the 2of12inf dictionary nor meet the threshold frequency. For example, sentiment words such as *revolve*, *dream*, *solves*, *quit*, and *ideal* have fewer or no inflectional form entries in the LM dictionary. As a result, certain sentiment words may not have equivalents in the ArFinSD, especially those that can be expressed in different POS. Accordingly, the word *dream* is captured through two distinct lemmas in Arabic: (verb) يَحلُم and (noun) حُلم; each of which represents an extensive set of morphologically related forms.

Another key factor contributing to the high volume of Arabic sentiment words is the ArFinSD's construction method used in this research. Arabic and English differ substantially in word usage; from a lexicon-based classification perspective, the ArFinSD captures a broader set of sentiment words in Arabic documents than the LM dictionary does in English documents. Due to Arabic lexical diversity, several Arabic words are often translated into a single distinct English word in the LM dictionary. During the translation and adaptation of the LM dictionary into Arabic, many English words were translated into multiple Arabic equivalents, each of which can be a counterpart to a single English word. The linguistic differences between Arabic and English demand the inclusion of multiple Arabic word candidates to accurately capture the meaning of corresponding English words in Arabic financial textual content. For instance, the verb *achieve* is translated as أَحْرَزَ, حَقَّق, and أَنْجَزَ in the ArFinSD. All three Arabic translations of the English word *achieve* convey the same meaning in Arabic financial settings. Another example is the negative word *costly,* which is translated into three Arabic equivalent terms in the ArFinSD: باهِظ, غالِي, and مُكَلِّف. However, these Arabic translations may be reflected in the

English version through the use of a synonym for the word *achieve* or *costly* that is not included in the LM dictionary.

Although the two dictionaries are relatively comparable in number of entries, they differ substantially in structure and coverage. For example, the ArFinSD contains 2,121 unique lemmatized negative sentiment words (unigrams, bigrams, and trigrams), and the LM dictionary contains 2,345 words, including inflections. Similarly, the ArFinSD contains 565 unique entries in the positive category, distributed across different n-gram levels (unigrams, bigrams, and trigrams). The LM dictionary contains only 347 entries, including inflected forms. However, the lemma-based matching can generate a considerable number of inflected forms corresponding to the lookup form in the ArFinSD. Therefore, considering all possible morphological inflections, the coverage of the ArFinSD categories significantly exceeds that of the LM dictionary. This results in more Arabic matches being identified when mapping these sentiment terms, thereby contributing to the higher frequency counts recorded in the Arabic reports.

It is important to note that specific Arabic sentiment terms are shared across multiple distinct English sentiment words, resulting in lexical overlap. A notable example is the word *challenge* and its inflected forms in the LM dictionary (challenges, challenging, challenge, and challenged) which appear 2,447, 584, 392, and 39 times, respectively, in the English annual reports. These inflected forms can be translated to تَحَدِّي, تَحَدَّى, إِعْتَرَض, صَعْب, and مُعَقَّد according to the ArFinSD. However, several of these Arabic translations are not exclusive to the word *challenge*. For example, the word مُعَقَّد is also a translation of the English words *challenging*, *complicated*, and *cumbersome*. Additionally, the word إِعْتَرَض corresponds to 13 other translations besides *challenge* and *challenged*, including *disagree*, *disagreed*, *disagreeing*, *disagrees*, *dispute*, *disputed*, *disputing*, *objected*, *objecting*, *oppose*, *opposed*, *opposes*, and *opposing*. Additionally, several of these English words, such as *oppose*, *opposed*, *opposes*, and *opposing*, can also be translated to مانَع, further contributing to the lexical overlap.

A common theme in Arabic sentiment classification compared to English sentiment classification is the high frequency of sentiment words in Arabic, despite the previous discussion of differences between English and Arabic in terms of morphological dissimilarity and the size of the ArFinSD in terms of unique word entries. However, at this stage, the construction of Arabic and English reports remains unclear. Questions such as whether firms write the Arabic version and subsequently translate it into English or whether they craft the English reports independently, remain ambiguous. This is critical because sentiment words in one version can be diluted, omitted, rephrased, or preserved in the corresponding report. The following examples illustrate how some sentiment words are expressed across the Arabic and English versions of annual reports. Each example highlights different linguistic and contextual phenomena contributing to such discrepancies in Arabic and English sentiment word identification:

Example 1: Arabic sentiment word (lemma): تَحَدِّي

- Original Arabic text:

"علـى الرغـم مـن البيئـة الاقتصاديـة غيـر المواتية، فقد اتسمت قطاعات أعمالنـا بفعاليتـها واستباقيتها فـي قـراءة معطيات السـوق وإجراءاتها العمليـة فـي مواجهـة التحديـات"

- Lemmatized Arabic text:

"عَلَى رَغْم مِن بِيئَة اِقْتِصادِيّ غَيْر مُواتِي، قَدْ اِتَّسَم قِطاع عَمَل فَعّالِيَّة اِسْتِباقِيّ فِي قِراءَة مُعْطَيات سُوق إِجْراء عَمَلِيّ فِي مُواجَهَة تَحَدِّي"

- English version:

"Despite the economic headwinds, our business segments were both reactive and proactive in their attitudes and actions."

In the Arabic text, the word "تَحَدِّي" (challenge) appears in the phrase " فـي مواجهـة التحديـات," which conveys challenges and struggles. The word "تَحَدِّي" aligns with the LM dictionary's negative sentiment category of challenge and corresponds to the word challenge and its inflected forms *challenge*, *challenging*, and *challenged*. In contrast, the English version omits the sentiment word "تَحَدِّي" from the text and removes any explicit reference to challenge; instead, the firm phrases the counterpart text as "reactive and proactive in their attitudes and actions."

Example 2: Arabic sentiment word (lemma): اِسْتِثْنائِيّ

- Original Arabic text:

"أضافت قطاعـات أعمالنـا الرئيسية، ممثلـة في البحـري للنفط والبحري للكيماويـات والبحـري للخدمـات اللوجستية والبحـري للبضائع السـائبة والبحـري للخدمـات البحريـة والبحـري لإدارة السفن، قيمة استثنائية إلى هـذا النجـاح سـواء علـى مستوى أعمالهـا الفردية أو على مستوى أعمال المجموعـة ككل."

- Lemmatized Arabic text:

"أَضاف قِطاع عَمَل رَئِيسِيّ ، مُمَثَّل فِي بَحْرِيّ نَفْط بَحْرِيّ كِيمِيائِيّ بَحْرِيّ خِدْمَة لُوجِسْتِيّ بَحْرِيّ بِضاعَة سائِب بَحْرِيّ خِدْمَة بَحْرِيّ بَحْرِيّ إِدارَة سَفِينَة ، قِيمَة ٱسْتِثْنائِيّ إِلَى هٰذا نَجاح سَواء عَلَى مُسْتَوَى عَمَل فَرْدِيّ أَو عَلَى مُسْتَوَى عَمَل مَجْمُوعَة كُلّ".

- English version:

"Our Oil, Chemical, Logistics, and Dry Bulk shipping, as well as Bahri Marine and Bahri Ship Management, added outstanding value both individually and collectively."

In the second example, the word "ٱسْتِثْنائِيّ" (exceptional) is expressed within the phrase "قيمة استثنائية إلى هذا النجاح" which conveys exceptional or outstanding value. The word ٱسْتِثْنائِيّ is categorized as a positive word in the ArFinSD and is the translation equivalent of the words *exceptional* and *exclusive* in the LM dictionary. The English version of the text expresses the word "ٱسْتِثْنائِيّ" as "outstanding," a semantically appropriate equivalent. Although the word "outstanding" maintains a positive tone in Arabic, it is not included in the LM dictionary. Loughran and McDonald (2015) noted that the word *outstanding* is extensively used in financial disclosures to refer to shares outstanding or options outstanding rather than to describe firm performance. The absence of such words creates a lexicon asymmetry when computing sentiment word frequencies, resulting in underrepresentation in the English version using the LM dictionary relative to the Arabic text using the ArFinSD.

Example 3:

Arabic sentiment words (lemmas): تَحْقِيق and ٱسْتِثْنائِيّ

- Original Arabic text:

"لقد نجحت شركة البحري خلال العام 2023 م في تحقيق إنجازات استثنائية وأداء قوي بفضل نهجها القيادي الناجح الذي اتسم بالفعالية في اتخاذ القرارات ووضوح الرؤية والأهداف الاستراتيجية. وأو أن أعرب عن خالص امتناني لزملائي في فريق الإدارة التنفيذية وجميع الموظفين على دعمهم الدائم والتزامهم القوي بجعل شركة البحري في مصاف الشركات الرائدة على مستوى العالم في مجال الشحن والخدمات اللوجستية".

- Lemmatized Arabic text:

"قَدْ نَجَح شَرِكَة بَحْرِيّ خلال عام 2023 م فِي تَحْقِيق إِنْجاز ٱسْتِثْنائِيّ أَداء قَوِيّ فَضْل نَهْج قِيادِيّ ناجِح الَّذِي ٱتَّسَم فَعّالِيَّة فِي ٱتِّخاذ قَرار وُضُوح رُؤْيَة هَدَف إِسْتراتِيجِيّ. وَدّ أَنَّ أَعْرَب عَن خالِص امتناني زَمِيل فِي فَرِيق إِدارَة تَنْفِيذِيّ جَمِيع مُوَظَّف عَلَى دَعْم دائِم ٱلْتِزام قَوِيّ جَعْل شَرِكَة بَحْرِيّ فِي مَصَفّ شَرِكَة رائِد عَلَى مُسْتَوَى عالَم فِي مَجال شَحْن خِدْمَة لُوجِسْتِيّ".

- English version:

"Bahri has just completed a year characterized by prosperous leadership and success and I would like to express my gratitude to my fellow members of the executive management team and all of our employees for their ongoing support and commitment in making Bahri a world-class shipping and logistics company."

In the Arabic version, the use of the words "تَحْقِيق" (achieve) and "ٱسْتِثْنائِيّ" (exceptional) conveys a positive tone, emphasizing the firm's achievement of its goals. Both of these sentiment Arabic words are present in the ArFinSD. In contrast, the English version of the text does not demonstrate a direct equivalent of the word "تَحْقِيق." Instead of expressing the word as "achievement" or "achieve," the firm phrases it in the English version as "a year characterized by prosperous leadership and success." Even though the term "success" maintains a positive tone, the absence of a direct English counterpart in the Arabic dictionary, where the term is explicitly identified, highlights lexical asymmetry.

Similarly, the word "ٱسْتِثْنائِيّ", which was translated as "outstanding" in Example 2, is not used as an equivalent translation of the Arabic but rather as a broader expression in "prosperous leadership and success." While the tone remains positive, the phrase does not indicate an exceptional or outstanding ability to achieve goals, as illustrated in the Arabic version. Likewise, this example introduces asymmetry and leads to inconsistencies in sentiment word identification across the two dictionary versions.

Example 4:

Arabic sentiment words (lemmas): تَمَيَّز

- Original Arabic text:

"الاستراتيجيات التي صممناها بعناية ونفذناها تحت إشراف مجلس إدارة يتميز برؤية ثاقبة أثمرت نتائجها بتحقيق نجاح يتجاوز النجاح المالي. لقد تماشينا استراتيجياً مع رؤية المملكة العربية السعودية 2030 مركزين على الحفاظ على البيئة، التأثير الاجتماعي، والحوكمة القوية."

- Lemmatized Arabic text:

"إِسْتراتِيجِيَّة الَّذِي صَمّ عِنايَة نَفَّذ تَحْتَ إِشْراف مَجْلِس إِدارَة تَمَيَّز رُؤْيَة ثاقِب أَثْمَر نَتِيجَة تَحْقِيق نَجاح تَجاوَز نَجاح مالِيّ. قَدْ تَماشَى إِسْتراتِيجِيّ مع رُؤْيَة مَمْلَكَة عَرَبِيّ سَعُودِيّ ٢٠٣٠ مُرَكَّز عَلَى حِفاظ عَلَى بِيئَة، تَأْثِير ٱجْتِماعِيّ، حوكمه قَوِيّ."

- English version:

"The strategies we meticulously designed and implemented under the guidance of a board with a visionary outlook have yielded results beyond financial success. We have strategically aligned with Saudi Arabia's Vision 2030, focusing on environmental conservation, social impact, and strong governance."

The Arabic word "تَمَيُّز" conveys excellence or distinction and is often used to highlight exceptional results or performance. The term تَمَيُّز in the ArFinSD aligns with the positive sentiment list in the LM dictionary which includes the words *excel* and *excelling*. However, in the English version, this sentimental word is omitted. The English phrase that corresponds to the Arabic term "تَمَيُّز" is "board with a visionary outlook." It is worthy of note that the Arabic and English versions are semantically equivalent, in which the firm utilizes the word "تَمَيُّز" to describe the board of directors regarding the attribute of possessing "a visionary outlook." Nevertheless, while the sentiment is conveyed in both corpora, the Arabic term is identified by the ArFinSD. In contrast, the LM dictionary does not capture the corresponding English expression.

Taken together, the sentiment distributions of annual reports and CEO letters in Arabic and English exhibit a high degree of positivity. According to the ArFinSD and LM dictionary, positive sentiment is the most dominant category in both Arabic and English documents. Across all sentiment categories, the most common words in Arabic and English remain similar but their frequencies show divergence. The construction approach used by ArFinSD, which includes more unique Arabic translations equivalent to English sentiment words, yields higher identification rates than in English documents. Additionally, the morphological complexity and structural differences between Arabic and English require lemma-level matching, thereby introducing additional forms that the LM dictionary does not capture. Moreover, a certain degree of language asymmetry is present in the Arabic versions of annual reports and CEO letters compared to their English equivalents.

5.3.2 Sentiment Classification Agreement: Arabic and English

While the previous section discussed sentiment word frequencies and composition between Arabic and English financial texts, this section evaluates the extent to which sentiment classification across the categories, including positive, negative, and uncertain, is associated between the Arabic and English versions of the same reports and CEO letters at the document level. The sentiment classifications are computed using the ArFinSD for Arabic documents and the LM dictionary for English equivalents, taking into account differences in dictionary design and language features. Additionally, we assess sentiment at the document level by comparing overall sentiment (*Tone*) and the share of sentiment for each annual report and CEO letter.

Table 5.3 provides a statistical summary of sentiment categories across annual reports and CEO letters in both languages, comparing the two settings. Accordingly, in annual reports, the mean share of positive sentiment words in Arabic is 4.20%, almost double the mean of 2.17% in English annual reports. In addition, negative sentiment words appear slightly more frequently in Arabic (2.34%) than in English annual reports (1.65%). Furthermore, the mean proportion of uncertain words is 1.80% in Arabic annual reports, compared to 1.85% in English annual reports. A similar pattern was observed across the CEO letters' sentiment categories, with greater positive sentiment dominance in both versions. The average positivity share in Arabic is 10.46%, whereas in English it decreases by approximately 38% to a mean of 6.52%. Moreover, negative sentiment is slightly higher in Arabic (1.79% vs 1.29%), whereas uncertainty words remain relatively low in both languages (0.69% vs 0.47%). To complement the descriptive statistics reported in Table 5.3, Figure 5.1 and Figure 5.2 illustrate the evolution of sentiment proportions in the Arabic annual reports and CEO letters and their English counterparts over the period 2018-2023. The figures provide insight into the patterns and directional changes in textual sentiment conveyed in the Arabic and English versions of corporate disclosures issued by firms listed on the Saudi Stock Exchange.

The preceding section highlighted linguistic and structural differences in the construction approach of the ArFinSD and in word representation (lemmatized vs inflected forms) in cross-language sentiment analysis settings. These differences account for divergence in sentiment identification across the Arabic and English reports and CEO letters. Nonetheless, both the ArFinSD and LM dictionary were developed with financial applications in mind. Therefore, whether the ArFinSD and LM dictionaries can consistently capture sentiment at the document level and produce similar tone assessments across English and Arabic documents remains a critical question. In other words, if a firm's report in English expresses a relatively high degree of positivity, does the Arabic counterpart report also indicate a relatively high positivity tone? Because both the LM dictionary and ArFinSD are designed for financial applications, the research aims to test whether cross-linguistic consistency holds across Arabic and English financial disclosures.

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Table 5.3 Arabic vs English Textual Sentiment Analysis

ArFinSD						English (LM dictionary)					Pairwise Corr.	Spearman Corr.
	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)		
Panel A: Annual reports N= 728												
POS	4.20	3.82	1.70	0.89	10.52	2.17	2.03	0.97	0.23	5.79	0.936***	0.930***
NEG	2.34	2.21	0.74	0.50	5.47	1.65	1.51	0.68	0.35	5.19	0.884***	0.864***
UNC	1.80	1.71	0.66	0.08	4.03	1.85	1.72	0.83	0.24	6.15	0.890***	0.890***
Panel B: CEO letters N= 274												
POS	10.46	10.76	2.88	2.92	20.76	6.52	6.32	2.25	1.60	15.44	0.701***	0.688***
NEG	1.79	1.55	1.31	0.00	7.05	1.29	0.89	1.26	0.00	9.30	0.741***	0.755***
UNC	0.69	0.61	0.54	0.00	2.76	0.47	0.41	0.45	0.00	2.39	0.404***	0.405***

The table presents summary statistics on the share of sentiment words in Arabic annual reports and CEO letters and their corresponding English versions, based on Loughran and McDonald (2011) (LM dictionary) and the ArFinSD. Additionally, the table reports pairwise (Pearson) and Spearman rank correlations based on the positive, negative, and uncertain sentiment categories, as defined in the LM and ArFinSD dictionaries. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

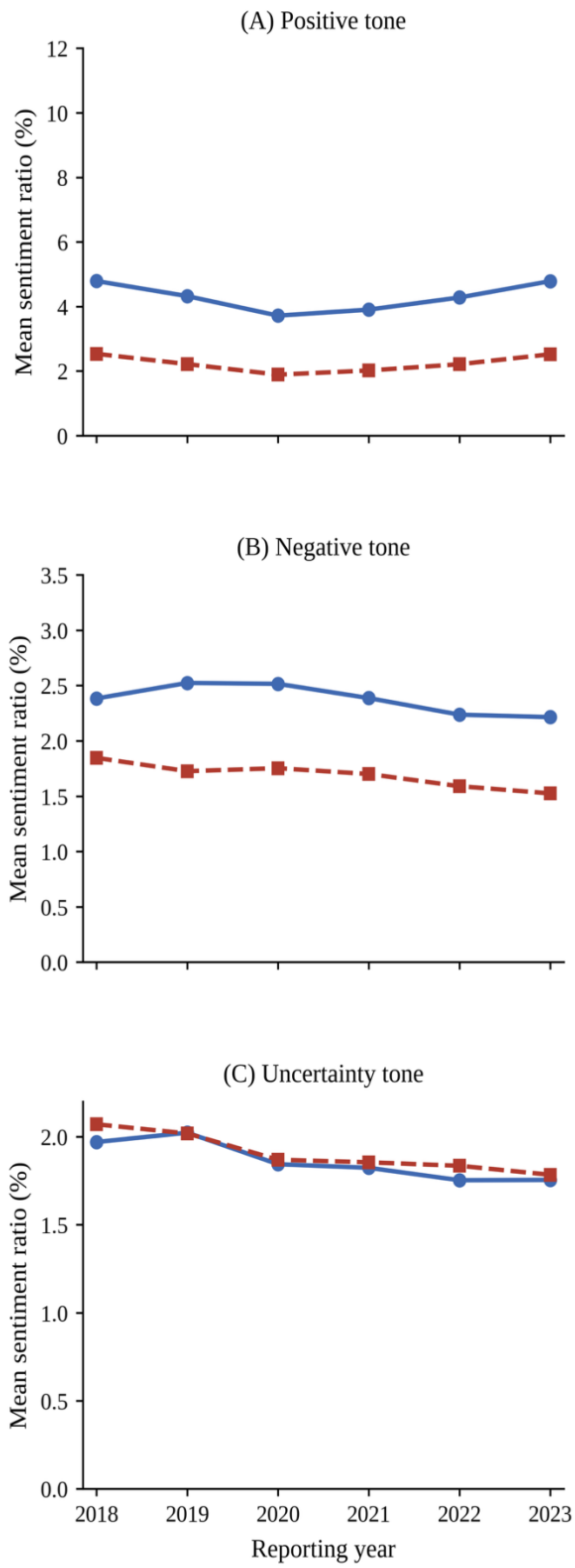

Figure 5-1. The annual evolution of positive, negative, and uncertainty sentiment proportions in the Arabic annual reports and their corresponding English versions over the period 2018-2023(N=728).

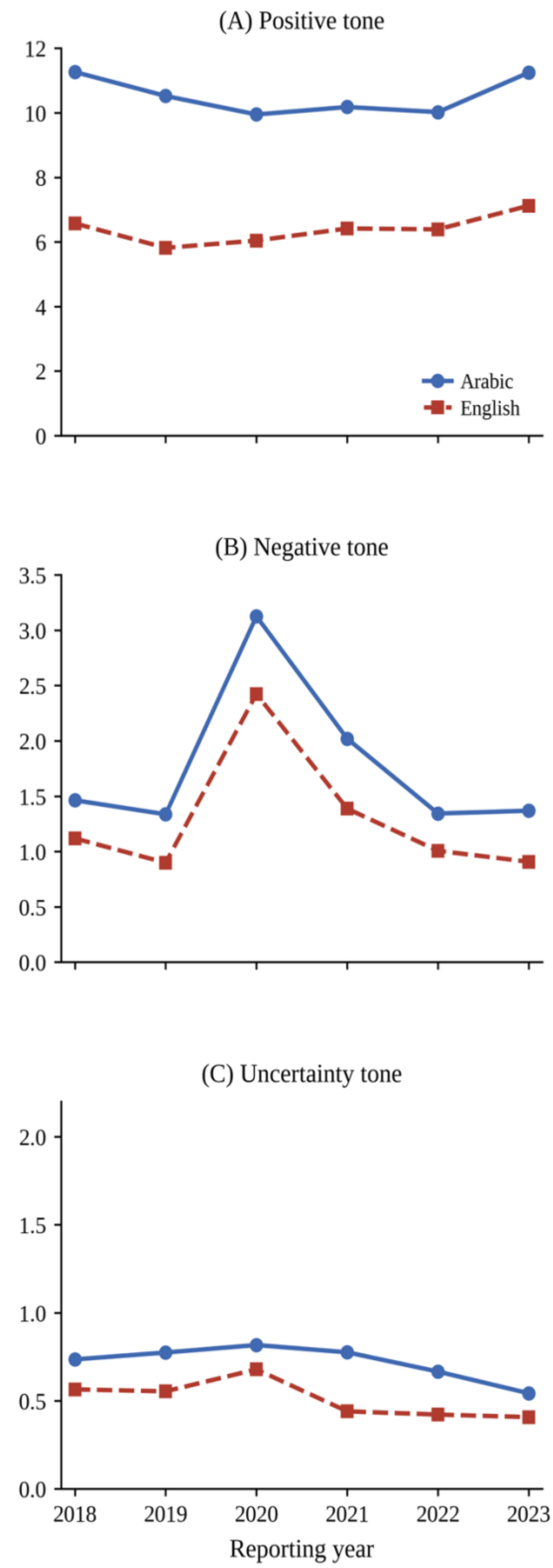

Figure 5-2. The annual evolution of positive, negative, and uncertainty sentiment proportions in the Arabic CEO letters and their corresponding English versions over the period 2018-2023(N=274).

Building upon established validation approaches, as illustrated in Chapter 3, Section 3.6, the research aims to assess whether the ArFinSD can produce results comparable to those of the LM dictionary using Arabic and English annual reports and CEO letters. Two statistical measures are applied to determine the cross-linguistic reliability of the sentiment classification: Pairwise and Spearman correlations. The correlation validation approach was initially employed by LIWC adaptation studies, such as that by Wolf et al. (2008). It was later replicated by Bannier et al. (2019) in their German adaptation of the LM dictionary. These metrics are used to assess the degree of agreement in sentiment proportions across the sentiment categories, including positive, negative, and uncertain in both Arabic and English texts. Correlation-based validation is among the most widely employed techniques for evaluating the reliability of sentiment dictionaries across languages. These statistical evaluations provide a robust assessment of whether sentiment classifications are preserved across languages despite lexical and structural differences.

Table 5.3 presents the correlation results between the sentiment classification categories produced by the ArFinSD and the LM dictionary across the annual reports and CEO letters. The results indicate a strong relationship between the Arabic and English sentiment categories across the annual reports. The pairwise correlation coefficients for the three sentiment categories (positive, negative, and uncertain) are high at 0.936, 0.884, and 0.890, respectively. These findings are stronger than those reported by Bannier et al. (2019), who observed Pairwise correlations of 0.839 (negative), 0.831 (positive), and 0.758 (uncertain) using German and English annual reports. In a similar validation approach, González et al. (2021) found a correlation of 0.82 for uncertainty and 0.7 for negative sentiment. However, when the authors combined the sentiment lists into one dictionary, they reported a correlation of 0.7. Additionally, Spearman rank correlations also confirmed strong consistency between Arabic and English sentiment categories when using the ArFinSD and LM dictionary, with correlations of 0.930 for positive sentiment, 0.864 for negative sentiment, and 0.890 for uncertainty. These findings exceed those reported by Bannier et al. (2019), who found Spearman rank correlations of 0.783 (negative), 0.819 (positive), and 0.740 (uncertain) using annual reports in German and English.

For the CEO letters, the correlation results, as presented in Table 4.3, are slightly lower than those observed for the annual reports. The Pairwise coefficients for positive, negative, and uncertainty categories are 0.701, 0.741, and 0.404, respectively. Similarly, the Spearman rank correlations are 0.688 for positive, 0.755 for negative, and 0.405 for uncertainty. Notably, the uncertain words in the CEO letters showed lower correlation coefficients in both measurements than those in the other sentiment categories. This may reflect the narrative style of the CEO letters or the uncertainty language expressed across Arabic and English. CEO letters are generally less technical than the other sections of annual reports and they are often influenced by the CEO. As a result, factors such as the CEO's culture, background, native language, and communication style can influence the narrative tone and content across both the Arabic and English versions. Whether CEO letters are composed in both languages independently or whether one version is translated from the other remains unclear. The uncertainty in authorship and the firm's translation practices may lead to inconsistent sentiment expression across the two versions, ultimately affecting the distribution of sentiment categories between the two letters. Additionally, the word *"may"* appears 62 times, accounting for 11.36% of the most frequent uncertain words in the English version of the CEO. In Saudi firms' disclosures, CEOs often close their letters with expressions such as "may Allah bless…" regarding the country's prosperity or its leadership.

Furthermore, to assess whether the overall sentiment classification at the document level (*Tone*) is preserved across the Arabic and English versions, the research computed sentiment tone for each annual report and CEO letter using a matrix that is widely used in dictionary-based sentiment analysis. The approach is adopted from Loughran and McDonald (2015), Davis et al. (2015), and Picault and Renault (2017). The overall *Tone* is defined as the net difference between the occurrences of positive and negative words, normalized by the total number of words in the document.

The correlation results indicate strong alignment in sentiment tone between Arabic and English, particularly in the annual reports. The Pearson correlation for the overall sentiment scores across the annual reports is 0.927 ($p < 0.001$), whereas the Spearman rank correlation is 0.926 ($p < 0.001$), both indicating a nearly one-to-one relationship between the Arabic and English annual reports, as measured by the ArFinSD and LM dictionary. Although the CEO letters are slightly lower than the annual reports, the correlation remains moderate, at 0.759 (Pearson) and 0.756 (Spearman), both of which are statistically significant at the 0.001 level. Figures 5.3 and 5.4 present the Tone distribution across the Arabic and English annual reports and CEO letters at the document level. The overall sentiment correlation results across the Arabic and English versions in both the annual reports and CEO letters confirm that the proposed ArFinSD dictionary can effectively capture the overall sentiment in Arabic financial text because it achieves a high degree of alignment with the sentiment tone expressed in the English versions using the LM dictionary.

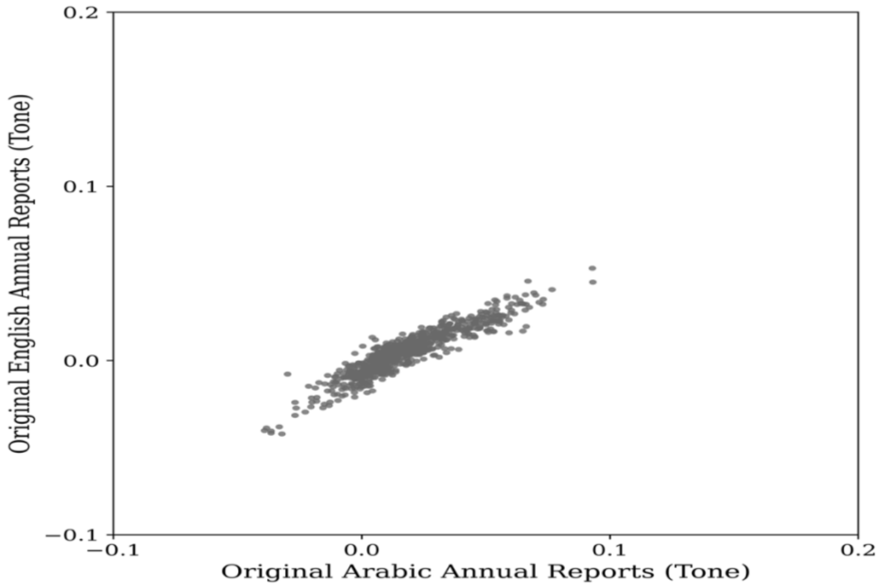

Figure 5-3. Overall Tone in Original Arabic and English Annual Reports

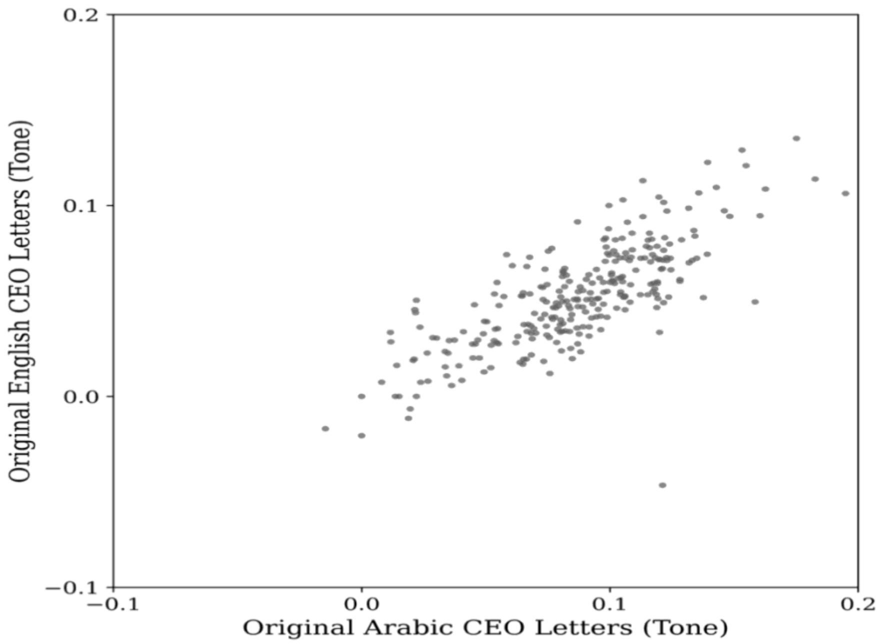

Figure 5-4. Overall Tone in Original Arabic and English CEO Letters

Taken together, the correlation results demonstrate that the ArFinSD is a reliable tool for sentiment classification in Arabic financial text. Despite the linguistic and structural differences between Arabic and English, as well as the dictionary construction methods (lemma versus inflection and n-gram entries versus single entries), ArFinSD consistently produces sentiment classifications on Arabic text that align closely with those generated using the LM dictionary for financial texts in the English language. The consistency is particularly strong across the annual reports, with high correlations in both category-level and overall sentiment. These correlations exceed those reported in previous LM dictionary adaptation studies (e.g., Bannier et al., 2019; González et al., 2021). Notably, the ArFinSD, although not directly equivalent to the LM, produced stronger correlations than those reported for German adaptations of the LM, demonstrating its ability to capture the tone of Arabic financial text.

In contrast, the CEO letters recorded lower correlation coefficients, specifically in the uncertain sentiment categories. This may be due to the nature of the CEO letters, which are highly influenced by the author's characteristics. Another reason may stem from the use of the uncertain word *may* in the English version of the CEO letters, which is often used to express gratitude toward the country or its leadership. Nevertheless, the overall patterns of the sentiment classification across Arabic and English indicate that the ArFinSD is reliable for tracking cross-language sentiment trends in financial applications, particularly in longer document formats such as annual reports.

5.4 Negation Handling in Arabic and English Financial Text

Negation plays a critical role in sentiment classification because it can significantly shift the polarity of words. In financial narratives, such as annual reports or CEO letters, the presence of negation can reverse the meaning of predefined positive or negative words. Additionally, negation forms differ significantly between Arabic and English texts due to their morphological differences. A key distinction is that Arabic negation is always conveyed by explicit forms, with the negator a separate cue that precedes the word. In contrast, in addition to conveying explicit negation forms, English negations can also be expressed implicitly, with the negator embedded within the word's root.

This section presents the findings regarding the impact of negation on Arabic and English financial texts and discusses their implications. The research applies the negation function described in Chapter 4, Section 4.5 to both textual datasets. It identifies negation forms with three window scopes and then flips the polarity of sentiment words accordingly. In addition, the negation effect was applied to both ends of the sentiment scale. The research employs the negation forms proposed by Loughran and McDonald (2011) (*no*, *not*, *non*, *neither*, *never*, and *nobody*) on the English versions of annual reports and CEO letters. For Arabic, the widely used explicit negation forms (لا-Laa, ليس-Laysa, لن-Lan, لم-Lam) were employed, along with five additional negation forms that suit Arabic financial language (بلا-Bla, دون-Dwn, غير-Gyr, عدم-Edm, عكس-Eks). Furthermore, the current analysis of the role of negation in financial sentiment extends the baseline sentiment analysis settings outlined in Section 5.3, in which the ArFinSD and LM dictionary are used to identify sentiment in Arabic and English documents, respectively.

Table 5.4 provides a statistical summary of the negation detection algorithm applied to the Arabic and English financial texts. The Arabic language exhibits more negation effects in annual reports and CEO letters than in their English counterparts. The number of negation instances affecting predefined sentiment words in Arabic annual reports was 11,518, whereas the English counterpart reports recorded only 1,718. Likewise, the negation cases in the CEO letters, although relatively shorter than those in the annual reports, follow a similar trend: the Arabic versions exhibit a higher rate of negation detection than their English counterparts. The number of negation instances in Arabic CEO letters is 191, whereas the English version recorded only 39. This suggests that negations have a greater impact on sentiment classification in Arabic financial texts than in English financial texts.

Table 5.4 Summary of Negation Detection in Annual Reports and CEO Letters

Language	Negation Instance	% of Total Words	% of Affected Pos	% of Affected Neg	% of Affected Sentiment Words
Panel A: Annual reports N=728					
Arabic	11,518	0.19	1.54	5.13	2.18
English	1,718	0.03	0.30	1.69	0.60
Panel B: CEO letters N=274					
Arabic	191	0.12	0.57	3.42	0.92
English	39	0.03	0.24	1.48	0.41

The table illustrates the number and proportion of sentiment words identified within the negation window for Arabic annual reports and CEO letters and their corresponding English versions. The analysis is conducted using the ArFinSD for Arabic disclosures and the LM dictionary for English disclosures. The negation instance refers to the sentiment words whose polarity was reversed due to the negation effect. The % of the total words reflects the share of negated sentiment words relative to the corpus size. The affected sentiment words are presented for each sentiment category, along with the overall percentage of the total sentiment words identified in the corpus.

Table 5.5 illustrates the impact of negation in shifting sentiment polarity across the Arabic and English reports and CEO letters. The research applied the negation effect to both sentiment directions, flipping positive words to negative and vice versa, based on predefined negation forms and negation cues within the defined window scope. In Arabic annual reports, 4,358 positive sentiment words were flipped to negative due to the negation effects, whereas 7,160 negative words were converted to positive. In contrast, the English counterpart reports reveal that the number of positive sentiment words flipped to negative was 352, whereas the number of negative sentiment words flipped to positive was 1,366. In the CEO letters, the Arabic versions showed 97 flipped instances from positive to negative and 94 flipped instances from negative to positive. In the English version, only 39 cases were recorded, with 18 sentiment words converted from positive to negative and 21 reclassified from negative to positive. The results provide insight into the importance of applying the negation effect on both sentiment categories because the two versions of the financial text demonstrate reverse sentiment at both ends of the sentiment scale.

Table 5.5 Impact of Negation on Sentiment Words in Annual Reports and CEO Letters

Language	Positive to Negative	Negative to Positive	Total Words Flipped
Panel A: Annual reports N=728			
Arabic	4,358	7,160	11,518
English	352	1,366	1,718
Panel B: CEO letters N=274			
Arabic	97	94	191
English	18	21	39

The table presents details of the number of sentiment words whose polarity was flipped by negation in Arabic annual reports and CEO letters, along with their corresponding English versions. The analysis was conducted using the ArFinSD for Arabic documents and the LM dictionary for English. The negation effect was applied to the positive and negative sentiment categories. Appendix C.5 provides further illustrative examples of negation instances across the Arabic annual reports and their English counterparts.

The Arabic text exhibits a higher rate of negation detection and a more pronounced shift in sentiment polarity compared to English. A key contributor to the dissimilarity negation detection between Arabic and English financial texts lies in the fact that negation forms differ morphologically. In Arabic financial text, the negator form is a separate token that precedes the sentiment words. Under the dictionary-based sentiment approach, it is easy to identify negation cues because the classification model includes a negation-form list; thus, handling negation is more efficient in Arabic, where the negator is expressed as a separate token. For example, in

Arabic annual reports, the negation forms were identified 21,150 times for لا-Laa, 13,948 times forغير-Gyr, 7,953 times for لم-Lam, 2,996 times forدون -Dwn, 1,323 times for ليس-Laysa, 415 times for لن-Lan, 290 times for عكس-Eks, and 85 times for بلا-Bla.

However, negation forms in English are not always presented as distinct cues and this can reduce the negation detection rate when relying on predefined form lists for matching. In the English annual report versions, negation forms were identified 18,202 times for *not*, 527 times for *none*, 165 times for *neither*, 76 times for *never*, and one time for *nobody*. The number of negation forms detected in the Arabic and English corpus does not indicate a direct sentiment shift because these instances are computed as a standalone list and do not contribute to the sentiment shift. However, successfully identifying more negation forms increases the likelihood that the model applies the negation window scope and, consequently, detects sentiment words in the vicinity of the negation.

More critically, the sentiment categories in the LM dictionary, particularly the negative list, contain a substantial number of sentiment words that exhibit implicit negation through morphological prefixes embedded within the words. Implicit negation forms such as dis-, im-, non-, ir-, or less are inherently embedded with the sentiment word and convey a negation attribution (e.g., disqualifies, disallows, noncompetitive, impermissible, irreversible, groundless). These words convey a negative sentiment due to a negation cue embedded in the root and inherently fulfill the role of the negation effect. The implicit negation in English enables dictionary-based sentiment analysis to capture negativity without relying heavily on an explicit list of negations. As a result, many negated sentiment words in English are effectively captured by matching their lexical forms. Hence, negation only affects 0.06% of the total English sentiment words identified in the annual reports and 0.41% in the CEO letters.

Arabic, on the other hand, cannot express negation as an implicit negator embedded with sentiment words. Hence, the Arabic sentiment classification employed n-gram modeling to address the ArFinSD, using bi- and trigram sentiment words as translation equivalents of English sentiment, including words with implicit negation. In the ArFinSD, a majority of two- and three-dimensional sentiment words stemmed from translations of English words with embedded implicit negators (e.g., dis-, im-, non-, less, etc.) or adverbs ending in *-ly*. To bridge the gap in the linguistic negation differences between Arabic and English, these words were translated into n-gram equivalents. For example, the negative word *irrecoverable* was translated into five equivalents, including *لا أَمْكَن تَعْوِيض*, *غَيْر قابِل ٱسْتِرْداد*, *غَيْر قابِل ٱسْتِعادَة*, *لا أَمْكَن ٱسْتِرْداد*, and *مُتَعَذِّر إِصْلاح*. However, negation can take various forms in Arabic, which complicates the accuracy of capturing the Arabic counterparts of English sentiment words. As a result, using the predefined negation list in Arabic financial texts significantly improves the accuracy of sentiment classification.

To that end, negation forms in Arabic can serve in other grammatical categories beyond their negation functionalities. This may lead to ambiguity regarding whether their occurrences align with the intended negation framework. For example, the negation form Maa-ما is considered a classical negation form in MSA texts such as annual reports and was excluded from the predefined Arabic negation list. This was mainly due to the multifunctionality of the form in formal communications. For example, based on the financial corpus in this study, the word *Maa-*ما was recorded 42,048 times within the Arabic annual reports. In many cases, managers in annual reports use the Arabic negative form *Maa-*ما to articulate visionary statements and it is rarely used to express negation.

Furthermore, in prior studies concerning English financial narratives, the application of negation handling has been inconsistent. Some researchers apply negation exclusively to positive words (Loughran & McDonald, 2011), arguing that firms are unlikely to use negated negatives to communicate good news and instead rely on direct positive words. Others apply negation to both positive and negative categories to capture the full scope of the polarity shifts in a narrative setting (Brau et al., 2016). These approaches are conducted relative to the linguistic and communicative styles of English financial disclosures. However, no prior research has thoroughly addressed the handling of negation in Arabic financial texts or its implications for sentiment classification.

Given the morphological and syntactic differences between Arabic and English, as demonstrated by variations in negation systems, including implicit and explicit negation cues, the analysis reveals that the negation effect is greater in Arabic corporate disclosures compared to their English counterparts. As shown in Table 5.5, there were 7,160 instances of negation in which negative words were converted to positive in Arabic and 4,358 instances in which positive words were converted to negative. In Arabic annual reports, companies often use negated negative terms to convey positive outcomes. For example, (there is no conflict) عَدَم وُجُود أَيّ عارَض, (not contradict) لا تَعارَض, (no damage) لا ضَرَّ, (without disruption) دُون إِخْلال, (without delay) دُون تَأْخِير are among the most frequent negated negative words. These negated terms are used to describe positive events or outcomes but they risk being mislabeled as negative if the negation effect applies only to the positive sentiment category.

Although more than 13,000 words in Arabic are affected by negation, the overall impact remains minimal at the document level. When comparing sentiment classification results before and after applying the negation algorithm, the assigned sentiment tone for each document changes only slightly. The small effect is due to the overall sentiment score calculation method, which determines the score as the difference between positive and negative sentiment counts, normalized by the length of the document. Consequently, negated sentiment words, regardless of their linguistic significance, result in minimal change when spread across a large document. In other words, the normalization framework dilutes the impact of shifting negations unless the count of negated sentiment words is especially high. However, flipping the sentiment due to negation remains crucial to accurately reflect the intended sentiment and avoid sentiment misclassification.

In contrast, English texts tend to incorporate negation as an embedded cue via morphological prefixes, which explains the low rate of negation detection. However, when applying the negation effect to words with negative sentiment, the results indicate that negated negatives are used throughout the English versions of the annual reports. Negated negative words, such as *not conflict*, *not harm*, *not exposed*, and *not contradict,* are among the most frequent negated negative words. Even though the negation effect is significantly lower in English reports than in their Arabic counterparts, the findings of the current research suggest that considering both ends of the sentiment scale in negation handling improves classification accuracy. Appendix C.5 offers a comprehensive list of negation examples, illustrating how negation operates within the sentiment classification framework.

5.5 When Meaning Shifts: Arabic Sentiment in General and Financial Dictionaries

The following sections present a comparative textual analysis utilizing the ArFinSD and ArSenL, an Arabic general sentiment dictionary (Badaro et al., 2014), to evaluate the accuracy of employing domain-oriented versus general dictionaries for sentiment analysis in Arabic financial contexts. In the current section, the research addresses the research question (*To what extent does the proposed Arabic financial sentiment dictionary yield accurate results in measuring sentiment compared to Arabic general dictionaries?*). It is well-documented in the English literature that finance-oriented dictionaries are able to more accurately measure tone in financial settings. More importantly, in the Arabic NLP literature, it is well established that domain-specific language poses challenges for sentiment analysis applications (Mao et al., 2024; Oraby et al., 2013; Wankhade et al., 2022). However, in Arabic, measuring textual sentiment in financial applications has received little attention and there is no established Arabic financial dictionary for sentiment analysis. More importantly, Arabic general dictionaries have not been evaluated and compared to Arabic finance-oriented dictionaries. Therefore, the comparative textual analysis compares the ArFinSD and ArSenL to evaluate the consistency of sentiment word classification. Additionally, the research conducts dictionary-based sentiment analysis of Arabic financial disclosures using both dictionaries to assess their ability to accurately gauge sentiment in financial narratives.

5.5.1 Comparative Analysis of Sentiment Classification: ArFinSD and ArSenL

This section presents a comparative cross-classification analysis of sentiment categories across the ArFinSD and general-purpose ArSenL lexicon. Table 5.6 illustrates the differences in sentiment assignments across the three sentiment categories (positive, negative, and uncertainty) in the ArFinSD relative to the ArSenL. The comparison procedure setup between the two dictionaries, including the pre-processing pipelines, is outlined in Chapter 4, Section 4.7. The comparison is conducted by matching the one-dimensional sentiment entries between the two dictionaries. The two- and three-dimensional entries are excluded from the comparison because ArSenL's construction approach is limited to a one-dimensional framework entry. Furthermore, the sentiment words were aligned at the lemma level because both dictionaries are constructed using the lemma forms of Arabic words. Figure 5-5 further demonstrates the distribution of sentiment classification agreements and discrepancies found between the two dictionaries.

Table 5.6 Cross-Classification of Sentiment Categories in ArFinSD and ArSenL

ArFinSD classification	ArSenL: Positive	ArSenL: Negative	ArSenL: Neutral
	n (%)	*n* (%)	*n* (%)
Positive (*n*=332)	237 (71.4)	45 (13.6)	50 (15.1)
Negative (*n*=1,028)	205 (19.9)	591 (57.5)	232 (22.6)
Uncertainty (*n*=165)	59 (35.8)	78 (47.3)	28 (17.0)

The table presents a cross-classification of one-dimensional sentiment words shared by the ArFinSD and the ArSenL. Rows correspond to a sentiment category according to the ArFinSD, while the columns indicate how the same sentiment words are classified by ArSenL. Values are reported as counts, with row percentages in parentheses. The *n* shown next to each ArFinSD category represents the number of entries in that category that are also found in ArSenL. For instance, 237 words are classified as positive in both dictionaries, whereas 45 are classified as negative by ArSenL. Since ArSenL does not include an uncertainty category, the shared ArFinSD uncertainty sentiment words are distributed across the positive negative and neutral categories, according to their ArSenL classifications.Words in the cross-classification categories comparison are provided in Appendix C.6.

The research reveals several inconsistencies in the sentiment categories between ArFinSD and ArSenL. Notably, of the 1,028 words identified as negative in ArFinSD, only 591 are also labeled as negative in ArSenL. Meanwhile, in ArSenL, 205 of these are classified as positive, whereas 232 are classified as neutral. Similarly, among the 332 positive words identified in ArFinSD, 45 are classified as negative and 50 as neutral by ArSenL. In the ArFinSD uncertain dictionary, 78 words are classified as positive and 28 as neutral in the general-purpose category (ArSenL). Recalling that overlap between negative and uncertain categories was allowed in the Arabic adaptation of the LM dictionary, an overlap between the ArFinSD uncertain list and the negative ArSenL list is justified because many ArFinSD uncertain list items are close to negative sentiment rather than positive. However, these misclassifications across all sentiment categories reveal a significant discrepancy in polarity between the two dictionaries.

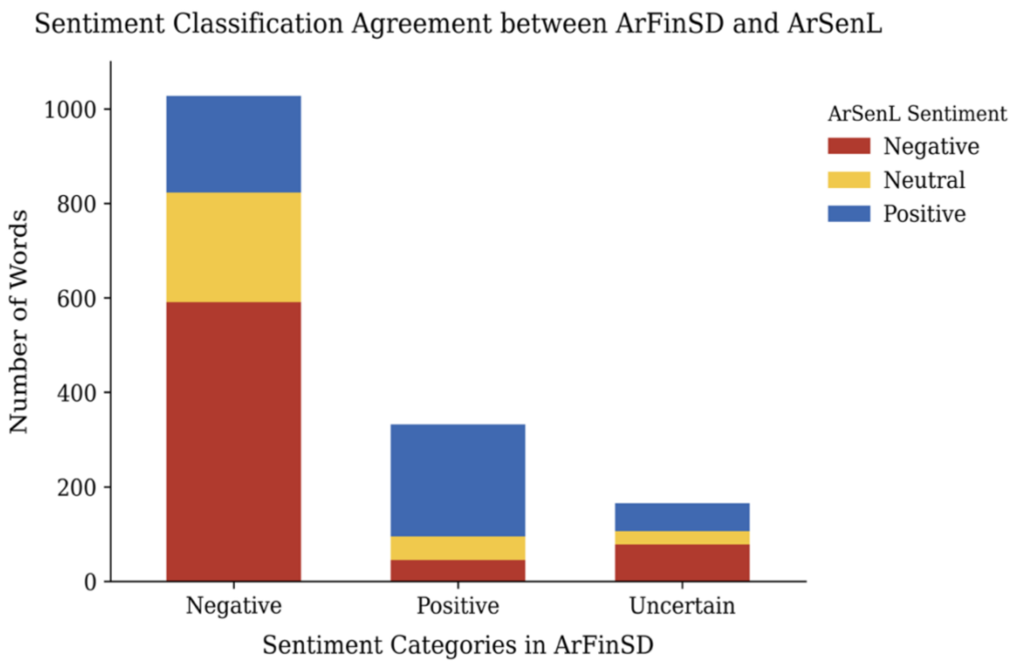

Figure 5-5. Distribution of sentiment categories assigned by ArSenL across each ArFinSD category

These classification inconsistencies have critical implications in financial settings. Negative words in finance carry more weight than positive sentiment (Loughran & McDonald, 2011). When investigating the ArFinSD miscategorized negative words in ArSenL, words were detected that are classified as neutral in ArSenL but convey negative meaning in financial applications. For instance, words such as تَذَبْذَب (volatility), إِجْبار (coercing; compulsion), إِخْلال (displacement), إِخْفاء (overrun), إِلْزام (compulsion; enjoining), إِنْهاء (termination; closure;

ceasing), تَأْجِيل (delay; postponement), تَأْخِير (delay), تَخْفِيض (downgrade; downsize), تَداعِي (fallout), and تَراجَع (dropped) introduce a negative connotation in the financial disclosures and convey strong negative sentiment rather than a neutral tone, according to ArSenL. In fact, these words clearly indicate adverse events, risks, or a decline in performance in a financial narrative. Treating these sentiment words as neutral diminishes the sentiment analysis's outcome, preventing it from fully capturing the true tone in Arabic financial text.

To that end, in financial applications, the sentiment scale is inherently polarized, ranging from positive to negative words. Consequently, there should be a significant semantic and contextual gap between words with opposing sentiment polarities. However, many Arabic words are polysemous, making sentiment orientation highly sensitive to the domain in which they are used. Words that exhibit positive sentiment in ArSenL and in general usage often adopt a negative connotation in financial narrative, particularly in corporate reports and business communications. For example, the word إِنْقاذ (bail; bailout) is generally associated with assistance or relief (rescue). However, financial narratives may indicate institutional failure or insolvency that requires external intervention. Similarly, بَراءَة (exculpating; acquittal) suggests justice or innocence in a legal setting, but when used in financial documents, it often conveys a negative sentiment because it is associated with reputational risk. Loughran and McDonald (2011) emphasized that negative words have a more pervasive influence, even when the term appears in phrases such as "whose *felony* conviction was overturned."

Further examples include تَحَوُّط (prevention) and تَرْشِيد (rationalization) are classified as positive in general applications. Nevertheless, in financial narratives, these words convey a negative connotation, potentially indicating cost-cutting measures or operational constraints. Likewise, words such as تَرَوِّي (caution) and حِيطَة (caution) indicate uncertainty, hesitation, or a lack of a strategic plan in Arabic business communication. In addition, the words غالِي (costly) and قَلَّل (degrade), which are both classified as positive in the general-purpose dictionary (ArSenL), are highly domain dependent. They carry significant negative connotations in Arabic financial disclosures, typically indicating decreased revenue and margins.

Uncertainty is another core element of financial communication, representing managers' risk evaluation and expectations. An uncertain sentiment wordlist enables testing of hypotheses beyond the positive-negative sentiment of financial narratives. Several studies in the English financial literature have demonstrated the economic significance of uncertainty in financial texts. Prior studies have leveraged textual uncertainty to examine a wide range of hypotheses. For example, studies examine and link uncertainty to loan contract terms, stock price crash risk, earnings volatility, market reactions to earnings announcements, information asymmetry, and abnormal returns (Demers & Vega, 2014; Dzieliński et al., 2017; Ertugrul et al., 2017; Loughran & McDonald, 2011; Black et al., 2025). These studies emphasize that the uncertain tone is a crucial textual measure indicator associated with different financial outcomes and market behaviors. Sentiment words such as may (رُبَّما), suggests (اِقْتَرَح), uncertainty (غُمُوض; تَرَدُّد; اِرْتِياب), unclear (غَيْر واضِح; مُبْهَم; غامِض), unknown (غَيْر مَعْرُوف; مَجْهُول), and unplanned (دُون تَخْطِيط; غَيْر مُخَطَّط; غَيْر مُتَوَقَّع), found in the ArFinSD, convey an uncertain tone in managerial communication and can serve as clues to information asymmetry, ambiguity, or managerial uncertainty caution. By explicitly tagging such uncertain words, researchers can empirically investigate how uncertainty tone in Arabic financial disclosures, such as annual reports, press releases, and earnings announcements, is associated with market behavior and corporate outcomes.

However, in Arabic, expressions of uncertainty are highly context-dependent and vary significantly across different domains. Words that may carry positive connotations in general settings and are also classified as positive in ArSenL often convey a cautious or ambiguous tone when used in financial narrative settings. For instance, the term إِمْكانِيَّة (possibility) generally indicates opportunity or potential in common Arabic interpretation, but in financial texts, it signifies a lack of clarity or uncertainty. Other terms that express uncertainty in Arabic financial language include مُتَغَيِّر (variable) and راجَع (revise), both of which are highly context-dependent. These terms do not necessarily imply ambiguous language outside the context of business communications. Similarly, the term مُتَوَقَّع (anticipated; predicted; predictive; presumed) conveys uncertainty in Arabic financial contexts, but it does not necessarily carry the same implication in general contexts. Moreover, تَحَسُّب (anticipate) and تَرَقَّب (anticipate) are commonly used in Arabic financial texts to reflect uncertainty or unexpected events. While, in general Arabic usage, these terms may convey different degrees of an anticipatory connotation, they demonstrate hesitation and ambiguity in tone when applied to financial contexts.

The inconsistencies in sentiment categorization underscore the limitations of relying on general sentiment dictionaries for domain-specific financial texts. They emphasize the need for a finance-oriented dictionary specifically designed to encompass the distinctive language and context of Arabic financial disclosures. A complete list of contradictions in sentiment words classification across the ArFinSD and ArSenL is provided in Appendix C.6.

5.5.2 Sentiment Analysis of Arabic Financial Text: ArFinSD and ArSenL

This section applies the sentiment general-purpose dictionary, ArSenL, to the Arabic annual reports and CEO letters to evaluate the impact of classification differences. The research aims to assess the capabilities of general-purpose dictionaries to accurately capture tone in Arabic financial settings for document-level sentiment classification, including the frequency of sentiment words across financial disclosures. Details of sentiment classification implementation, the pre-processing steps, and comparative setup are provided in Chapter 4, Section 4.7.

Table 5.7 presents the distribution of sentiment across positive, negative, and neutral categories in Arabic annual reports based on the ArSenL general dictionary. The ArSenL dictionary contains approximately 7.7 times as many sentiment words as the ArFinSD dictionary, resulting in a higher sentiment identification rate. A significant size difference is expected between a domain-oriented dictionary and a general-purpose dictionary. For example, the authors of the BPW dictionary reported that the general-purpose dictionary SENTIWS contains 6.9 times as many positive words as their finance-oriented dictionary (Bannier et al., 2019). The number of one-dimensional words that overlap between the ArFinSD and ArSenL dictionaries is very high across all sentiment categories. Specifically, the ArFinSD negative list overlaps with 94.1%, the positive list overlaps with 94.5%, and the uncertain list overlaps with 92.4% of the ArSenL lexicon, resulting in an overall coverage rate of approximately 94%. The high level of overlap was expected, considering the comprehensive construction of ArSenL, which leverages AWN and ESWN to expand lexical coverage.

According to Table 5.7, applying the ArSenL dictionary to the annual reports reveals a considerably inflated matching count: positive words are identified 2,639,655 times, negative words 1,004,882 times, and neutral words 2,190,067 times across the annual report corpus. In comparison, the ArFinSD identifies 282,927 positive words, 139,645 negative words, and 104,580 uncertain words, as demonstrated in Table 5.1. Given that the ArSenL provides broader coverage, it can significantly increase the sentiment detection rate while obscuring important patterns in domain-specific language. For example, positive matches exceed 2.6 million occurrences, nearly nine times those identified by the ArFinSD.

Table 5.7 Most Frequent Sentiment Words in Arabic Annual Reports (ArSenL)

Rank	Word	Total	%	Cum%	Rank	Word	Total	%	Cum%
Panel A: Most common positive words									
1	عَلَى	149,657	5.58	5.58	11	كان	22,183	0.83	20.74
2	إدارَة	106,380	3.97	9.55	12	داخِلِيّ	21,898	0.82	21.56
3	مالِيّ	53,544	2.0	11.55	13	تَنْفِيذِيّ	21,724	0.81	22.37
4	عَمَل	53,094	1.98	13.53	14	قِطاع	20,875	0.78	23.14
5	تَمّ	43,413	1.62	15.15	15	سِياسَة	20,504	0.77	23.91
6	خِدْمَة	28,229	1.05	16.2	16	هَدَف	19,347	0.72	24.63
7	نِظام	28,221	1.05	17.26	17	رِبْح	19,229	0.72	25.35
8	مُكافَأَة	25,316	0.94	18.2	18	مُساهِم	19,137	0.71	26.06
9	مَجْمُوعَة	23,539	0.88	19.08	19	عَمِيل	18,944	0.71	26.77
10	قِيمَة	22,255	0.83	19.91	20	أَداء	18,831	0.7	27.47
					All		2,639,655		
Panel B: Most common negative words									
1	ما	42,246	4.14	4.14	11	مِعْيار	13,259	1.30	23.38
2	عامّ	36,929	3.62	7.76	12	خاصّ	13,129	1.29	24.67
3	كَما	22,636	2.22	9.98	13	أُخْرَى	12,511	1.23	25.89
4	قام	21,068	2.07	12.05	14	تِجارِيّ	11,168	1.10	26.99
5	مَمْلَكَة	20,390	2.00	14.05	15	عَدَد	10,559	1.04	28.02
6	إِجْراء	18,671	1.83	15.88	16	بُعْد	9,938	0.97	29.00
7	سَنَوِيّ	17,382	1.70	17.58	17	اِجْتِماع	9,840	0.96	29.96
8	مِلْيُون	16,748	1.64	19.23	18	عالَمِيّ	9,406	0.92	30.89
9	تارِيخ	14,664	1.44	20.67	19	تابِع	9,069	0.89	31.78
10	سَهْم	14,425	1.41	22.08	20	تَكْلِيف	9,024	0.88	32.66
					All		1,004,882		
Panel C: Most common neutral words									
1	فِي	235,177	10.74	10.74	11	سُوق	21,768	0.99	36.20
2	شَرِكَة	185,032	8.45	19.19	12	عَمَلِيَّة	20,437	0.93	37.13
3	مَجْلِس	73,219	3.34	22.53	13	تَقْرِير	18,972	0.87	38.00
4	الَّذِي	71,113	3.25	25.78	14	شَكْل	18,190	0.83	38.83
5	لَجْنَة	43,890	2.00	27.78	15	بَنْك	18,103	0.83	39.65
6	عُضْو	37,051	1.69	29.47	16	نِسْبَة	16,528	0.75	40.41
7	عام	36,377	1.66	31.13	17	اِسْتِثْمار	16,219	0.74	41.15
8	مُراجَعَة	36,204	1.65	32.79	18	مُوَظَّف	16,191	0.74	41.89
9	أَيّ	29,430	1.34	34.13	19	تَطْوِير	15,819	0.72	42.61
10	سَعُودِيّ	23,489	1.07	35.20	20	جَمْعِيَّة	15,251	0.70	43.31
All					All		2,190,067		

This table presents the 20 most frequent positive, negative, and neutral sentiment words found in the Arabic annual reports. The occurrences of Arabic words were calculated using the ArSenL dictionary, which is converted into a dominant sentiment orientation, as detailed in Chapter 4 Section 4.7.1. Sentiment words with equal negativity and positivity scores were classified as neutral. The dictionary contains lemma entries and duplicate lemmas were resolved by relying on the average score of the sentiment. An extended list of the most frequent sentiment words is provided in Appendix C.7.

Likewise, the count of negative words is approximately seven times larger than that identified using the domain-specific dictionary. Neutral terms account for more than 2.1 million matches, representing almost 37% of all tokens in the reports. Overall, the combined positive, negative, and neutral classifications with ArSenL exceed 5.8 million-word occurrences, which is approximately 97% of the six million tokens in the entire corpus of annual reports (excluding stop words; Chapter 4, Table 4.1). These scale differences indicate that much of the detected sentiment results from high-frequency, generic words rather than meaningful sentimental attributes. Therefore, relying on these inflated sentiment counts makes it challenging to differentiate between routine corporate reporting phrases and text that genuinely reflects managerial tone.

To that end, the most frequently identified positive words in ArSenL highlight the limitations of applying a general-purpose dictionary to financial narratives. As shown in Table 5.7, words such as عَلَى (on), تَمّ (has been: done), and كان (was) account for a substantial proportion of positive word occurrences, representing 5.58%, 1.62%, and 0.83% of the total positive words. However, these words are primarily function words or grammatical particles and do not indicate the tone of the managers in financial disclosures. Other frequently used positive words identified by ArSenL, including إِدارَة (management), مالِيّ (financial), نِظام (system), and عَمَل (work), are neutral terms that usually describe organizational activities and structures and their extensive use is anticipated in Arabic financial disclosures. Similarly, خِدْمَة (service) and قِطاع (sector) are generic business terms that reflect the nature of corporate reporting rather than expressing sentiment. A further example highlighting the importance of domain-specific interpretation is the word مُساهِم (shareholder), which occurred 19,137 times. In Arabic general narratives, the word مُساهِم (shareholder) often carries a positive connotation stemming from its Arabic root meaning ‘contributor.’ However, in corporate reporting, the term is used as a neutral reference or address to the firm’s shareholders, with no underlying indication of sentiment. This pattern indicates that a significant proportion of words identified as positive by the ArSenL dictionary are, in fact, neutral in business communications, underscoring the risk of overestimating sentiment when relying on general-purpose dictionaries to gauge sentiment in Arabic financial narratives.

Additionally, in the ArSenL lexicon, many sentiment words carry little to no sentiment attribution in financial applications. When examining the 20 most frequently used negative words, the majority of these words are misaligned with corporate reporting language. For instance, high-frequency words such as سَهْم (share; stock), سَنَوِيّ (annual), and مِلْيُون (million) are factual descriptors of equity instruments, reporting periods, or quantities, which do not inherently signal negative sentiment in financial settings. Similarly, words such as تارِيخ (data) and عَدَد (number) are common references to time and quantity and are considered natural in business and general-domain usage. Even words such as مِعْيار (standard) and تِجارِيّ (commercial) do not carry negative connotations and are frequently used to describe operational aspects of the business environment. While words like تَكْلِيف (cost) may carry negative connotations in certain contexts, such as increased expenses, their use in financial discussions typically indicates standard accounting terminology rather than sentiment. The 20 most frequently used negative words according to ArSenL account for more than one-third of the total count of negative words appearing in the annual report sample. In addition, the extensive coverage in the ArSenL lexicon may underestimate the presence of negative connotation words that can help to identify the managerial tone in business communications.

To provide insight into the issue of overstating and inconsistency in sentiment classification using the general dictionary, the top ten negative words identified by the finance-oriented dictionary, ArFinSD, were evaluated against their rankings and classifications in ArSenL (see Table 5.1 and Table 5.7). The research relies on sentiment analysis conducted in Section 5.3, which employed the ArFinSD to gauge sentiment across the Arabic annual reports. Only four of the ten most common words identified as negative by ArFinSD align with their ArSenL classification. These include خَسارَة (loss), تَعْوِيض (reparation), سَلْبِيّ (adverse; negative), عارَض (contradict), and مُواجَهَة (confrontation). More importantly, several of the most frequently occurring negative words in the finance-oriented dictionary ArFinSD are misclassified in ArSenL. For instance, the second most frequently occurring negative word, based on ArFinSD, اِنْخِفاض (decline), is classified as neutral by ArSenL. Similarly, negative words such as تَقْلِيل (deprecation), تَخْفِيض (downgrade; downsize), and تَنازُل (abandoned; abdicating; conceding) are classified as neutral in ArSenL. Moreover, according to ArFinSD, negative words such as تَحَدِّي (challenge) and خَضَع (subjected; subjecting) are predominantly positive according to ArSenL. These words carry negative connotations in business communications and misinterpreting them can directly affect the accuracy of sentiment classification, thereby complicating the assessment of tone in financial texts.

Furthermore, several sentiment words in ArSenL are considered stop words in financial settings and they do not convey a managerial tone. This phenomenon is common in general-purpose dictionaries, not only in Arabic but also across languages. According to the ArSenL sentiment classification of the Arabic annual reports, the most frequently occurring words across all sentiment categories in ArSenL include high-frequency function words that are typically treated as stop words in financial writing. Examples include عَلَى (on), which appears

149,657 times in the positive category, ما (what; that; not) which is recorded 42,246 times in the negative category, and فِي (in) with 235,177 occurrences in the neutral category. This pattern aligns with observations in English sentiment analysis studies. For instance, Loughran and McDonald (2015) reported that when applying Diction pessimism and optimism wordlists to assess the accuracy of gauging sentiment, function words such as *no* and *not* accounted for nearly 45% of all pessimistic words identified in annual reports. This is important because stop words are inherently domain-specific and terms that carry significant connotations in one field may not carry the same degree of significance in another. Function words and common connectors frequently appear in financial narratives as part of standard corporate reporting language, without conveying any sentiment. Hence, the sentiment identification rate is inflated by ArSenL's inclusion of such words. Therefore, applying general-purpose sentiment dictionaries without considering domain-specific usage can significantly affect the accuracy of sentiment classification in identifying the managerial tone in financial settings.

Likewise, the dictionary-based sentiment classification of Arabic CEO letters reveals similar patterns. Table 5.8 presents the most frequently occurring words identified by the ArSenL dictionary in the Arabic CEO letters. The results further illustrate that applying a general-purpose sentiment dictionary can not only inflate the sentiment measure by classifying common functional language and regular business terms but also misclassify sentiment words in financial narratives. The distribution of sentiment across the three categories in the CEO dataset, according to the ArSenL, remains significantly high. In total, the ArSenL dictionary identified 159,161 words, with the positive category having the highest number of occurrences (74,535), followed by the neutral category (56,446), and the remaining 28,180 labeled as negative. The sentiment words identified by ArSenL account for 98.29% of the CEO corpus, excluding stop words (see Chapter 4, Table 4.2).

Table 5.8 Most Frequent Sentiment Words in Arabic CEO Letters (ArSenL)

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
Panel A: Most common positive words									
1	عَلَى	4,451	5.93	5.93	11	إِسْتراتِيجِيّ	718	0.96	19.45
2	عَمَل	1,685	2.25	8.18	12	هَدَف	654	0.87	20.32
3	خِدْمَة	1,367	1.82	10.00	13	أَداء	652	0.87	21.19
4	قِطاع	1,107	1.48	11.48	14	كان	640	0.85	22.05
5	تَحْقِيق	1,094	1.46	12.94	15	مُسْتَوَى	628	0.84	22.88
6	عَمِيل	1,000	1.33	14.27	16	مالِيّ	628	0.84	23.72
7	جَدِيد	890	1.19	15.46	17	دَعْم	613	0.82	24.54
8	مَجْمُوعَة	764	1.02	16.47	18	قِيمَة	608	0.81	25.35
9	تَعْزِيز	761	1.01	17.49	19	مَجال	526	0.70	26.05
10	إِدارَة	754	1.01	18.49	20	نَجاح	493	0.66	26.71
All							74,535		
Panel B: Most common negative words									
1	عامّ	1,168	4.11	4.11	11	قام	333	1.17	25.12
2	مَمْلَكَة	1,029	3.62	7.72	12	عَدَد	326	1.15	26.26
3	ما	1,007	3.54	11.26	13	مُقارَنَة	304	1.07	27.33
4	كَما	848	2.98	14.25	14	رِعايَة	301	1.06	28.39
5	مِلْيُون	687	2.42	16.66	15	بُعْد	290	1.02	29.41
6	رَقَمِيّ	525	1.85	18.51	16	عَدِيد	289	1.02	30.42
7	عالَمِيّ	451	1.59	20.09	17	خاصّ	288	1.01	31.44
8	رُؤْيَة	372	1.31	21.40	18	حَلّ	275	0.97	32.40
9	مِلْيار	367	1.29	22.69	19	شُكْر	267	0.94	33.34
10	مُسْتَمِرّ	357	1.26	23.95	20	تِجارِيّ	266	0.94	34.28
All							28,180		
Panel C: Most common neutral words									
1	فِي	8,681	15.38	15.38	11	اِسْتِثْمار	584	1.03	37.89
2	شَرِكَة	3,287	5.82	21.20	12	مُنْتَج	538	0.95	38.84
3	الَّذِي	2,221	3.93	25.14	13	مُوَظَّف	531	0.94	39.78
4	عام	2,114	3.75	28.88	14	عَمَلِيَّة	526	0.93	40.71
5	نُمُوّ	1,132	2.01	30.89	15	تَأْمِين	486	0.86	41.57
6	تَطْوِير	725	1.28	32.17	16	بَرْنامَج	466	0.83	42.40
7	نِسْبَة	699	1.24	33.41	17	بَلَغ	433	0.77	43.17
8	سُوق	693	1.23	34.64	18	أَكْثَر	420	0.74	43.91
9	سَعُودِيّ	643	1.14	35.78	19	شَكْل	394	0.70	44.61
10	زِيادَة	606	1.07	36.85	20	واصَل	393	0.70	45.30
All							56,446		

This table presents the 20 most frequent positive, negative, and neutral sentiment words found in the Arabic CEO letters. The occurrences of Arabic words were calculated using the ArSenL dictionary, which is converted into a dominant sentiment orientation, as detailed in Chapter 4, Section 4.7.1. Sentiment words with equal negativity and positivity scores were classified as neutral. The dictionary contains lemma entries and duplicate lemmas were resolved by relying on the average score of the sentiment. An extended list of the most frequently used sentiment words is provided in Appendix C.8.

In comparison, the ArFinSD identifies 16,882 positive words, 2,746 negative words, and 1,103 uncertain words, as outlined in Table 5.2. The differences in words identified by the two dictionaries highlight how general-purpose lexicons can generate large volumes of sentiment matches, even though most of these do not express a sentiment attribute. Although CEO letters are generally less technical and predominantly narrative in nature compared to annual reports, the expected overlap between ArSenL and the finance-focused dictionary ArFinSD in terms of the most frequently occurring words remains limited. Only a few words, such as تَحْقِيق (achieve) and تَعْزِيز (enhance) in the positive category, appear as high-frequency words in both dictionaries. The remaining high-frequency words identified by ArSenL, including عَمَل (work), خِدْمَة (service), and عامّ (general), are routine expressions in corporate reporting that do not convey sentiment in a financial application context.

5.5.3 Sentiment Classification Agreement: ArFinSD and ArSenL

Lastly, the sentiment classification comparison of the Arabic finance-oriented dictionary (ArFinSD) and the general-purpose dictionary (ArSenL) was extended by computing pairwise and Spearman correlations across the positive and negative sentiment categories identified in Arabic annual reports and CEO letters. A low association was expected in sentiment classification, given the distinct domain orientations of the dictionaries. Nonetheless, because the ArSenL was constructed using multiple lexical resources, a substantial number of sentiment words in the ArFinSD overlap with those in the ArSenL. Consequently, the observed correlation across the two dictionaries may arise from the lexical overlap rather than agreement in sentiment interpretation.

Table 5.9 presents the descriptive statistics of positive and negative sentiment words across both annual reports and CEO letters, along with the pairwise and Spearman rank correlation coefficients. Because the ArFinSD includes a dedicated uncertainty list that lacks equivalents in ArSenL, and ArSenL includes neutral categorization that is absent in ArFinSD, comparisons were primarily conducted on the positive and negative word lists to maintain consistency. Furthermore, sentiment analysis using the ArFinSD was conducted on the Arabic baseline analysis presented in Section 5.3.

Table 5.9 Arabic Finance-Oriented Dictionary vs General Dictionary

ArFinSD						ArSenL					Pairwise Corr.	Spearman Corr.
	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)		
Panel A: Annual reports N: 728												
POS	4.20	3.82	1.70	0.89	10.52	39.29	39.48	2.43	24.16	45.60	0.379***	0.365***
NEG	2.34	2.21	0.74	0.50	5.47	15.28	15.27	1.22	10.31	19.50	0.307***	0.263***
Panel B: CEO letters N:274												
POS	10.46	10.76	2.88	2.92	20.76	41.80	42.11	4.30	27.49	54.46	0.432***	0.476***
NEG	1.79	1.55	1.31	0.00	7.05	15.72	15.71	2.38	9.09	22.86	0.322***	0.321***

The table presents summary statistics on the share of positive and negative sentiment words in Arabic annual reports and CEO letters using the ArFinSD and the ArSenL. The sentiment classification based on the ArFinSD follows the baseline analysis outlined in Section 5.3. Additionally, the table reports pairwise (Pearson) and Spearman rank correlations for the positive and negative categories, as defined in the ArFinSD and ArSenL dictionaries. The neutral category ArSenL and the uncertain category in ArFinSD are excluded, as neither has a direct corresponding sentiment category across the two dictionaries. The sentiment entries in ArSenL consist of one-dimensional lemma forms, whereas entries in ArFinSD include lemmas with up to three levels of dimensionality. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The results show that, despite the correlations being statistically significant at the 1% level, their magnitudes are consistently low. For instance, in the annual reports, the Pearson correlations for the proportions of positive and negative sentiment are 0.379 and 0.307, respectively, while the Spearman correlations are 0.365 and 0.263, respectively. In the CEO letters, they are slightly higher but still moderate associations, with Pearson correlations of 0.432 for positive sentiment classification and 0.322 for negative sentiment classification, and Spearman correlations of 0.476 and 0.321, respectively. Although all coefficients are statistically significant, these results indicate that the degree of shared variance between the two dictionaries is limited.

The modest alignment is noteworthy given the high degree of overlap between the one-dimensional entries in ArFinSD and ArSenL (over 90%). As previously discussed, high lexicon overlap alone does not imply strong convergence in the sentiment measurement. The limited correlation between the finance-oriented and general-purpose dictionaries is due to many shared words being assigned to different sentiment categories, leading to different aggregations of positive and negative proportions. Additionally, the ArSenL includes a much broader set of generic and high-frequency words that often appear in financial writing, reflecting the managerial tone. For example, based on the annual reports dataset, the most occurring sentiment words according to ArSenL are function words that do not convey meaning in the business communication (e.g., ما, فِي, عَلَى, and كان). Consequently, the sentiment measure derived from the ArSenL is systematically inflated and less reflective of the managerial tone.

Furthermore, the low correlation between the two dictionaries is unsurprising given that general sentiment resources often misclassify tone in particular domains, such as finance. In this matter, the findings regarding Arabic are consistent with those in the English literature which has demonstrated that general-purpose dictionaries are inappropriate for assessing textual sentiment in business communication. The textual comparison analysis in this research shows that nearly all high-frequency sentiment words identified by ArSenL are either basic functional words or are misclassified within the context of financial domain interpretations.

Additionally, the research does not examine the precision of sentiment classification across the complete set of ArSenL entries, rather it restricts the comparison to sentiment words overlapping with the ArFinSD. An increase in instances of sentiment misclassification in ArSenL should be anticipated when considering its application within the financial narrative. It is worthy of note that more than 600 words in ArFinSD are misclassified in ArSenL within the subset of the shared sentiment words (based on one-dimensional word comparison; see Table 5.6), suggesting that a larger proportion of ArSenL's entries, which were not examined, likely contain further terms whose sentiment labeling may be inconsistent and misclassified in financial applications.

The comparison becomes particularly apparent when comparing these results with the prior agreement analysis of the ArFinSD and LM dictionary in Section 5.3.2. Because both dictionaries are designed for a financial application, the comparison analysis yields notably strong results. The Pearson and Spearman correlation coefficients exceed 0.8 across sentiment categories in the annual reports and remain moderately strong in the shorter narratives of the CEO letters, both positive and negative. Although the two dictionaries are not directly equivalent, as discussed in Section 5.3.1, the substantially higher correlation between ArFinSD and LM dictionary suggests that specialized dictionaries are more accurate for gauging tone in financial narratives.

In conclusion, the textual comparative analysis demonstrates that a finance-oriented dictionary is superior to general-purpose lexicons for gauging sentiment in financial settings. The Arabic general sentiment dictionary employed in the current research significantly overestimates positivity and negativity in financial narratives, as indicated by the rate of sentiment-word identification. A major contributor to this trend is the inclusion of non-sentimental words, such as function words and generic terms that lack connotation, which can affect the accurate assessment of tone in Arabic business communication. Importantly, the analysis shows that ArSenL misclassifies a substantial number of one-dimensional pre-classified entries in the ArFinSD. These words account for almost 35% of the one-dimensional lemma entries in the ArFinSD. This finding is in accordance with the broader sentiment analysis literature in the finance field (Loughran & McDonald, 2011, 2015; Bannier et al., 2019) which emphasizes that the meaning of words is sensitive to the domains in which they appear and that finance-oriented sentiment dictionaries are more suitable for precisely gauging the tone in financial disclosures. Measuring the tone of Arabic financial sentiment requires a finance-oriented dictionary that accurately reflects the sentiment of words in the finance domain, whereas general-purpose dictionaries fail to capture the tone in financial narratives.

5.6 Translation's Impact on Sentiment in Financial Texts: Sentiment Analysis Results

The research aims to answer the following question: *To what extent does machine translation between Arabic and English affect the sentiment of financial disclosures?* Although previous studies have addressed the scarcity of linguistic resources for targeted languages by translating texts into resource-rich languages such as English, the impact of such translations on sentiment, particularly within the context of Arabic financial narratives, remains insufficiently explored. Advances in MT systems have improved the reliability of automated translation, as discussed in Chapter 2, Section 2.6. However, previous Arabic studies evaluating sentiment shifts across languages have primarily focused on informal or social media domains (e.g., Mohammad et al., 2016), rather than on formal business communication. The effect of MT on sentiment analysis in Arabic financial texts remains underexplored and the previous studies offer a limited understanding of how translation may influence sentiment shifts in this context. In the domain of business communication, it remains an open question whether automatic translation alters sentiment in financial settings.

To address this gap, this section provides a comprehensive textual analysis of the impact of MT on sentiment in financial texts. It primarily includes analysis and discussion of the annual reports. However, the same MT impact analysis was also conducted on the CEO letters; the results and comparative statistics for the CEO letters are provided in Appendix C.13 which demonstrates patterns similar to those in the annual reports. The bidirectional translation impact assessment experiment design is detailed in Chapter 4, Section 4.8. Furthermore, the dictionary-based sentiment classification settings follow the pre-processing pipelines and implementations for each language, as outlined in Chapter 4, Sections 4.4 and 4.5.

Recall that the translation impact assessment follows the bidirectional effect experiment design, as discussed in Chapter 4, Section 4.8. The sentiment classification results established in the baseline analysis, presented in Section 5.3, constitute the original sentiment classification that corresponds to the translation experiment design steps (A) and (E). These collectively demonstrate the firm's sentiment classification of its original documents in their representative language. The following sections conduct sentiment analysis on the translated annual reports in their new perspective language, corresponding to the experiment design steps (C) for Arabic and (G) for English. Together, these demonstrate the sentiment analysis of the translated annual reports after MT in their new language. The results are presented in a comparison setting, in which (A) is compared with (C), corresponding to step (D), to evaluate the extent of sentiment loss between the original Arabic financial disclosures and their English-to-Arabic counterparts. Similarly, Steps (E) and (G) address step (H) to evaluate the extent of sentiment loss between the original English financial disclosures and their Arabic-to-English counterparts.

5.6.1 Sentiment Analysis of Arabic Financial Text: Original and Machine Translated from English

Using the dictionary-based approach, Table 5.10 presents sentiment classification of the Arabic original and translated annual reports across three sentiment categories using the ArFinSD. The positive sentiment distribution, as shown in panel A, remains highest among the three categories across both the original and translated Arabic reports, with a total of 282,927 sentiment words identified in the original Arabic reports and 274,796 in the translated Arabic reports. Notably, there is a slight increase in the identification of positive words in the original Arabic annual reports. The Arabic original reports contain approximately 2.9% more positive words than the translated Arabic reports. Interestingly, the set of the most common sentiment words in both versions is preserved, albeit with a slightly different order. The ten most common words account for 36.97% in the original reports and 36.52% in the translated reports. For instance, the term تَحْقِيق (achieve) is the most frequent positive word in the original reports, with 16,828 occurrences. At the same time, it remains among the top 10 most frequent words in the translated reports, ranking second, with 14,133 occurrences. This pattern persists across the most frequently identified positive words, with minor variations in ranking and frequency.

Additionally, Panel B of Table 5.10 illustrates the distribution of the most frequently identified negative words across the Arabic original and translated annual reports. The total number of negative sentiment words is relatively close across the two versions, with 139,645 occurrences in the original Arabic reports and 140,272 occurrences in the translated reports, corresponding to a negligible reduction of only 627 in the translated dataset. In the original Arabic reports, the word خَسارَة (loss) is the most frequently identified negative word, accounting for 5.86% of all negative word occurrences with a total frequency of 7,431. This pattern is reflected in the translated Arabic reports, where the same word خَسارَة remains among the most common words identified, with a slightly lower frequency of 7,355, accounting for 5.74% of the negative words.

Table 5.10 Most Frequent Sentiment Words in Annual Reports (Arabic)

Rank	Arabic original reports				Translated Arabic reports			
	Word	Total	%	Cum%	Word	Total	%	Cum%
Panel A: Most common positive words								
1	تَحْقِيق	16,828	5.86	5.86	تَطْوِير	15,337	5.51	5.51
2	تَطْوِير	15,819	5.51	11.36	تَحْقِيق	14,133	5.08	10.58
3	نُمُوّ	11,890	4.14	15.50	نُمُوّ	11,286	4.05	14.64
4	تَعْزِيز	11,499	4.00	19.51	تَعْزِيز	11,083	3.98	18.62
5	دَعْم	9,777	3.40	22.91	تَحْسِين	9,598	3.45	22.07
6	قُدْرَة	9,434	3.28	26.19	دَعْم	9,549	3.43	25.50
7	تَحْسِين	8,875	3.09	29.28	قُدْرَة	8,741	3.14	28.64
8	ضَمان	8,431	2.93	32.22	ضَمان	8,731	3.14	31.77
9	كَفاءَة	7,015	2.44	34.66	أَعْلَى	6,739	2.42	34.19
10	أَعْلَى	6,627	2.31	36.97	كَفاءَة	6,478	2.33	36.52
All		282,927				274,791		
Panel B: Most common negative words								
1	خَسارَة	7,431	5.86	5.86	خَسارَة	7,355	5.74	5.74
2	ٱِنْخِفاض	5,079	4.01	9.87	ٱِنْخِفاض	4,431	3.46	9.20
3	تَحَدِّي	3,407	2.69	12.55	تَعْوِيض	3,872	3.02	12.22
4	تَعْوِيض	2,904	2.29	14.84	تَقْلِيل	3,319	2.59	14.81
5	تَقْلِيل	2,744	2.16	17.01	تَحَدِّي	3,079	2.40	17.22
6	خَضَع	2,037	1.61	18.62	ٱِعْتِراف	2,637	2.06	19.27
7	سَلْبِيّ	1,983	1.56	20.18	تَخْفِيف	2,243	1.75	21.03
8	تَخْفِيض	1,686	1.33	21.51	خَضَع	1,992	1.55	22.58
9	عارَض	1,655	1.31	22.81	سَلْبِيّ	1,922	1.50	24.08
10	مُواجَهَة	1,545	1.22	24.03	ٱِنْخِفاض قِيمَة	1,523	1.19	25.27
All		139,645				140,272		
Panel C: Most common uncertain words								
1	مَخاطِر	44,938	51.97	51.97	مَخاطِر	44,300	51.22	51.22
2	مُتَوَقَّع	4,586	5.30	57.28	مُتَوَقَّع	4,913	5.68	56.90
3	مُقْتَرَح	2,995	3.46	60.74	قَدَّر	3,070	3.55	60.45
4	تَعَرَّض	2,684	3.10	63.84	مُحْتَمَل	2,843	3.29	63.74
5	مُحْتَمَل	2,677	3.10	66.94	مُقْتَرَح	2,761	3.19	66.93
6	تَوَقَّع	2,662	3.08	70.02	تَعَرَّض	2,593	3.00	69.93
7	قَدَّر	2,353	2.72	72.74	تَوَقَّع	2,304	2.66	72.60
8	مُتَغَيِّر	1,749	2.02	74.76	مَعْقُول	1,693	1.96	74.55
9	مَعْقُول	1,579	1.83	76.59	مُتَغَيِّر	1,648	1.91	76.46
10	إِيضاح	1,406	1.63	78.21	أَظْهَر	1,297	1.50	77.97
All		104,580				104,001		

This table presents the most frequent sentiment words, categorized as negative, positive, and uncertain, identified in the annual reports for both the Arabic original reports and the machine-translated Arabic reports (from English). The translated Arabic annual reports were generated using the Google Cloud Translation API. The occurrences of Arabic words were computed using the ArFinSD. Additionally, all pre-processing steps and sentiment analysis procedures were applied identically to both textual datasets. An extended list of the most common Arabic translated sentiment words is provided in Appendix C.9.

Additionally, the most common negative words, although their rank order differs, remain largely unchanged, with a few notable exceptions. For example, the two-dimensional word اِنْخِفاض قِيمَة (deprecation) in the translated reports ranked tenth, with 1,523 occurrences, whereas the same entry appeared only 457 times in the original annual reports. Another example is the word عارَض (disfavor; dissent; contradict), which occurred 1,655 times in the original reports, ranking ninth among the most frequent words, whereas its counterpart occurred just 561 times in the translated versions of the annual reports.

Panel C of Table 5.10 presents the frequency and distribution of the most commonly observed words according to the uncertainty word list across the original and translated Arabic versions of the reports. Sentiment classification reveals a high degree of similarity between the two datasets, characterized by almost identical dominant words identified across the two corpora. In the original Arabic reports, the term مَخاطِر (risk) accounts for 51.97% of all uncertainty words, appearing 44,938 times. In the translated Arabic reports, the same word is also among the most frequently occurring words, accounting for 51.22% (44,300 occurrences) of the uncertainty words identified within the reports. Other uncertainty words, such as مُتَوَقَّع (anticipated; predicted; presumed; probable), مُقْتَرَح (suggested), and مُحْتَمَل (conceivable; contingent; possible; presumably; probabilistic; probable), continue to show high dominance, maintaining similar ranks and frequencies across both datasets.

The overall uncertainty word distribution remains relatively similar across the original and translated annual reports. The cumulative percentage of the top ten occurring words in the uncertainty category was 78.21% in the original reports and 77.97% in the translated Arabic reports, highlighting their dominance in indicating an uncertainty tone in the financial disclosures. Notably, limited variations are observed in the rank order and frequency of uncertain words. For example, the word مُتَوَقَّع (anticipated; predicted; presumed; probable) increases from 5.30% with 4,586 instances in the original reports to 4,913 instances (5.68%) in the translated versions, whereas the word قَدَّر (approximate) shifts from being seventh in rank in the original (2,662 times and 3.08%) to the third most frequent word in the translated version, occurring 3,070 times and accounting for 3.55%.

5.6.2 Sentiment Analysis of English Financial Text: Original and Machine-Translated from Arabic

Using the dictionary-based approach, Table 5.11 presents the frequency and distribution of the most common sentiment words across the three categories (positive, negative, and uncertainty) using the LM dictionary. The sentiment analysis includes both the original English annual reports and their machine-translated English counterparts (from Arabic). It is worthy of note that the LM dictionary includes inflected forms of words (e.g., loss, lose, and loses). Panel A of Table 5.11 illustrates the positive sentiment categories across the datasets, which remain the most dominant identified list in both the original and translated English reports. In the original English annual reports, positive words were identified 117,137 times. In contrast, the translated versions contained 140,095 occurrences of positive words, reflecting a notable increase of approximately 19.6% over the Arabic version when translated into English using MT.

The most common positive words are largely consistent across both versions, albeit with notable differences in frequency. According to the original reports, the word *achieve* appears 5,493 times (4.68%), followed by the word *best* (5,004; 4.26%), *efficiency* (4,216; 3.59%), and *opportunities* (3,920; 3.34%). In the translated versions of the annual reports, these words record different frequencies; for example, *achieve* appears 8,452 times (6.02%), *best* 6,055 times (4.31%), *efficiency* 5,511 times (3.92%), and *opportunities* 4,444 times (3.16%). Despite the most common positive sentiment words being similar across the two corpora, all positive words appear at higher frequencies in the translated reports than in their original English counterparts.

Panel B of Table 5.11 presents the distribution of the most frequently occurring negative words identified in both the original and translated English versions of the annual reports using the LM dictionary. The total number of negative words increases from 80,869 in the original English reports to 84,460 in the translated English reports, resulting in an approximate 4.4% increase. The word *loss* is the most frequently occurring negative term in both datasets, appearing 4,145 times (5.22%) in the original reports and 3,975 times (4.78%) in the translated reports. Likewise, the word *losses*, the inflected form of the word *loss*, appears 2,835 times (3.57%) in the original reports and 3,641 times (4.38%) in the translated versions.

Table 5.11 Most Frequent Sentiment Words in Annual Reports (English)

Rank	English original reports				Translated English reports			
	Word	Total	%	Cum%	Word	Total	%	Cum%
Panel A: Most common positive words								
1	achieve	5,493	4.68	4.68	achieve	8,452	6.02	6.02
2	best	5,004	4.26	8.94	achieving	6,256	4.45	10.47
3	efficiency	4,216	3.59	12.53	best	6,055	4.31	14.78
4	opportunities	3,920	3.34	15.87	efficiency	5,511	3.92	18.70
5	enhance	3,403	2.90	18.77	enhance	5,173	3.68	22.39
6	strong	3,274	2.79	21.56	opportunities	4,444	3.16	25.55
7	achieving	3,122	2.66	24.22	achieved	4,440	3.16	28.71
8	improve	3,108	2.65	26.87	strong	4,099	2.92	31.63
9	leading	3,008	2.56	29.43	improve	3,769	2.68	34.31
10	achieved	2,874	2.45	31.88	enhancing	3,637	2.59	36.90
All		117,137				140,095		
Panel B: Most common negative words								
1	loss	4,145	5.22	5.22	loss	3,975	4.78	4.78
2	losses	2,835	3.57	8.79	losses	3,641	4.38	9.16
3	against	2,550	3.21	12.00	challenges	2,989	3.59	12.75
4	challenges	2,447	3.08	15.08	conflict	2,237	2.69	15.44
5	claims	1,890	2.38	17.46	claims	2,103	2.53	17.97
6	conflict	1,499	1.89	19.35	exposed	2,009	2.42	20.39
7	impairment	1,485	1.87	21.22	against	1,856	2.23	22.62
8	exposed	1,469	1.85	23.07	negative	1,621	1.95	24.57
9	negative	1,123	1.42	24.49	decline	1,473	1.77	26.34
10	weaknesses	975	1.23	25.72	impairment	1,378	1.66	28.00
All		80,869				84,460		
Panel C: Most common uncertain words								
1	risk	27,995	33.66	33.66	risk	24,503	28.31	28.31
2	risks	17,901	21.52	55.18	risks	22,948	26.51	54.82
3	may	13,655	16.42	71.60	may	15,519	17.93	72.75
4	could	2,015	2.42	74.02	possible	2,053	2.37	75.12
5	possible	1,887	2.27	76.29	exposure	1,780	2.06	77.18
6	exposure	1,807	2.17	78.46	approximately	1,624	1.88	79.06
7	approximately	926	1.11	79.57	fluctuations	1,535	1.77	80.83
8	believes	918	1.10	80.67	could	1,408	1.63	82.46
9	precautionary	867	1.04	81.71	precautionary	1,182	1.37	83.82
10	fluctuations	851	1.02	82.73	believes	1,091	1.26	85.08
All		86,033				89,376		

This table presents the most frequently occurring sentiment words, categorized as negative, positive, and uncertain, identified in the annual reports for both the original English reports and the machine-translated English reports (from Arabic). The translated English annual reports were generated using the Google Cloud Translation API. The occurrences of English words were computed using the LM Dictionary. Additionally, all pre-processing steps and sentiment analysis procedures were applied identically to both textual datasets. An extended list of the most frequently occurring English translated sentiment words is provided in Appendix C.10.

The rank order and word identification of the top-most negative words remain broadly consistent between the two datasets. However, there are slight shifts in their individual frequencies and cumulative percentages. For example, the word *claims* appears 1,890 times (2.38%) in the original reports and 2,103 times (2.53%) in the translated reports. Similarly, the word *conflict* shifts from 1,499 occurrences (1.89%) in the original reports to 2,237 occurrences (2.69%) in the translated reports. The cumulative percentage of the top ten negative words is 27.17% in the English original version of the reports and 28.95% in the Arabic-to-English reports.

Panel C of Table 5.11 presents the distribution of the most common uncertainty words identified in the original English annual reports and their counterparts in the translated versions, along with their frequencies. The total number of uncertainty words increases from 86,033 in the original reports to 89,376 in the translated versions, reflecting an increase of approximately 3.9%. The word *risk* remains the most dominant uncertainty term in both datasets, with 27,995 occurrences (33.66%) in the original English reports and 24,503 occurrences (28.31%) in the translated English reports. In addition, the word *risks* appears 17,901 times (21.52%) in the original reports and 22,948 times (26.51%) in the translated counterparts. The terms *risk* and *risks* collectively constitute 55.18% of all uncertainty sentiment words in the original English annual reports and 54.82% in the translated versions. All high-frequency uncertain words identified across both datasets remain identical, although their frequencies and proportions shift between the original and translated corpora.

The cumulative distribution of the top ten uncertainty words is 82.73% in the original annual reports and 85.08% in the translated reports. Several terms, such as *fluctuations* (851 times in the original reports and 1,535 in the translated version) and *approximately* (926 times in the original reports and 1,624 in the translated version), exhibit increased frequencies in the translated corpus. In contrast, others, such as *could* (2,015 times in the original reports and 1,408 in the translated version), demonstrate a reverse effect. Furthermore, the words *believes* (918 times in the original reports and 1,091 in the translated version) and *possible* (1,887 times in the original reports and 2,053 in the translated version) record only moderate changes across the two versions of the annual reports. Despite these variations, both corpora display consistent identification of high-frequency uncertainty words, with adjustments in their relative frequency and ordering.

5.6.3 Sentiment Classification Agreement Between Original and Machine-Translated Documents

Following the descriptive and frequency analysis of sentiment distributions, this section evaluates the extent to which sentiment is preserved during MT. Specifically, the study assesses agreement between the original annual reports and their corresponding translations by measuring the consistency of sentiment classification at the category level (positive, negative, and uncertainty) and the overall sentiment (*Tone*) at the document level. The current section addresses steps (d) and (h) in the experiment design to assess the MT of Arabic and English financial texts. The research employs the evaluation methodology extensively used in cross-linguistic adaptation studies of sentiment dictionaries, particularly when mapping sentiment dictionaries from one language to another. These studies, as discussed in Chapter 3, Section 3.6, employed a set of statistical agreement measures to validate the reliability and equivalency of the sentiment dictionary across two languages (e.g., Boot et al., 2017; Wolf et al., 2008). In the current evaluation framework, the impact of translation on sentiment is assessed within the same language (e.g., original English vs translated English). Pearson's correlation and Spearman's rank correlation, as well as intraclass correlations (ICC [3,2]) after Shrout and Fleiss (1979) are employed to evaluate the degree of agreement between the two sentiment classification outcomes, which empirically assesses the extent of sentiment loss during the translation process. Additionally, the research applies the two-sided equivalence test, following the approach of Blair and Cole (2002), to assess sentiment equivalence between the original annual reports and their translations in each language.

The results of the sentiment classification agreement between the original and machine-translated annual reports in each language are summarized in Table 5.12. Additionally, it provides descriptive statistics summaries for each sentiment category (positive, negative, and neutral) in both the original and translated datasets, across Arabic and English annual reports. The table also provides Pearson correlations, Spearman rank correlations, and intraclass correlations (ICC [3,2]) after Shrout and Fleiss (1979) at the categorical sentiment class level.

Table 5.12 Original vs Machine-Translated Annual Reports Textual Sentiment Analysis

	Original annual reports					Machine-translated annual reports					Pairwise Corr.	Spearman Corr.	ICC [3,2]
	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)			
Panel A: Arabic language; N=728													
POS	4.20	3.82	1.70	0.89	10.52	4.40	4.06	1.68	1.64	11.04	0.976***	0.976***	0.988***
NEG	2.34	2.21	0.74	0.50	5.47	2.43	2.30	0.79	0.45	6.32	0.944***	0.933***	0.970***
UNC	1.80	1.71	0.66	0.08	4.03	1.88	1.80	0.66	0.20	4.59	0.966***	0.969***	0.983***
Panel B: English language; N=728													
POS	2.17	2.03	0.97	0.23	5.79	2.37	2.15	1.13	0.41	6.91	0.969***	0.975***	0.979***
NEG	1.65	1.51	0.68	0.35	5.19	1.61	1.50	0.68	0.42	4.96	0.972***	0.960***	0.986***
UNC	1.85	1.72	0.83	0.24	6.15	1.82	1.71	0.81	0.26	6.95	0.975***	0.971***	0.987***

The table presents summary statistics regarding the share of sentiment words in the original and machine-translated annual reports. The Arabic language annual reports classification is based on the ArFinSD, whereas the English language reports are classified based on the LM dictionary. Additionally, the table reports simple pairwise (Pearson) correlations, Spearman rank correlations, and ICC between the original reports and their translated versions within the same language. The correlations relate to negative, positive, and uncertain sentiment words identified based on the LM dictionary for English annual reports and the ArFinSD for Arabic annual reports. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.6.4 Sentiment Classification Agreement in Arabic Financial Documents

The analysis of the sentiment categories between the original Arabic annual reports and their Arabic translated counterparts (translated from the corresponding English reports), as presented in Table 5.12, reveals a high degree of consistency across all sentiment categories. For positive sentiment, the Pearson correlation coefficient is 0.976 ($p<0.001$) and the Spearman rank correlation is also 0.976 ($p<0.001$). Additionally, the ICC [3,2] is estimated at 0.988 ($p<0.001$), indicating high consistency between the positive sentiment proportions across the Arabic original version and their translated Arabic counterparts. For negative sentiment, the Pearson correlation coefficient is 0.944 and the Spearman rank correlation is 0.933 (both $p<0.001$). Similarly, the ICC [3,2] is estimated at 0.970 ($p<0.001$), further supporting the high degree of consistency between the two versions of the Arabic reports. For uncertainty sentiment, the Pearson correlation coefficient is 0.966 ($p<0.001$), while the Spearman rank correlation coefficient is 0.969 ($p<0.001$). Additionally, the ICC [3,2] is estimated at 0.983 ($p<0.001$) for the uncertainty category across the two versions. A visual comparison of the original and translated Arabic annual reports across sentiment categories (positive, negative, and uncertain) is presented in Figure 5.10.

To further assess the impact of translation on sentiment in Arabic-English financial settings, a two-sided equivalence test was conducted following the approach of Blair and Cole (2002). The equivalence test assesses whether the differences in sentiment proportions identified in the original annual reports and their machine-translated versions are statistically equivalent, using a predefined equivalence margin of ± 0.25 standard deviations. Each sentiment category (positive, negative, and uncertainty) is measured as the proportion of sentiment words in that category to the total number of words in each document (without the stop words). As illustrated in Figure 5-6, the 90% confidence intervals for the three sentiment categories fall within the equivalence area, indicating that the sentiment words identified in the original Arabic reports are statistically equivalent to those in their Arabic translated versions.

Additionally, sentiment preservation was evaluated based on tone at the document level. The overall sentiment tone was calculated as the difference between the positive and negative sentimental words, normalized by the total number of words in each report. Figure 5.7 displays the overall tone relationship between the original Arabic annual reports and their machine-translated counterparts, indicating a high level of correspondence between the two versions of the report. The Pearson correlation coefficient is 0.977 and the Spearman correlation coefficient is 0.975; both are statistically significant at $p < 0.001$.

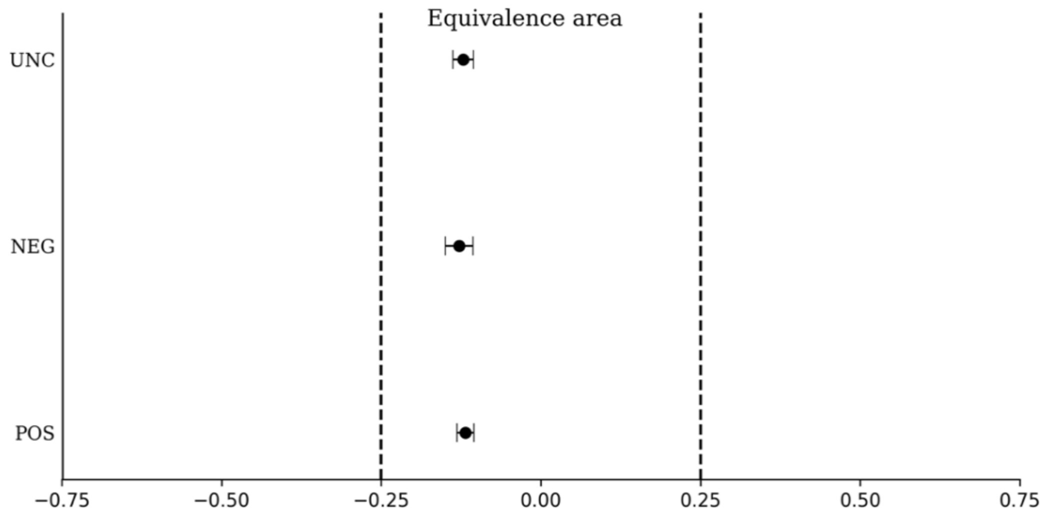

Figure 5-6. Two-sided equivalence test for the sentiment proportions between the original Arabic annual reports and their Arabic translations of the corresponding English versions

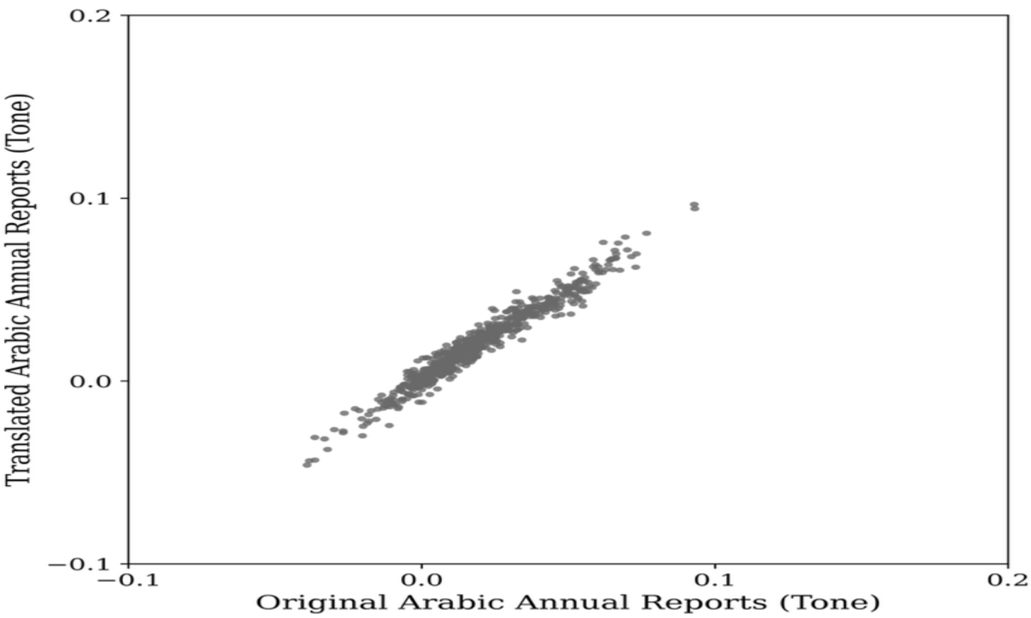

Figure 5-7. The overall sentiment (Tone) in the original Arabic annual reports and their machine-translated Arabic counterparts

5.6.5 Sentiment Classification Agreement in English Financial Documents

The analysis of the sentiment categories between English annual reports and their English translated counterparts, as shown in Table 5.12, reveals a high level of consistency across all sentiment categories. For positive sentiment, the Pearson correlation coefficient is 0.969 (p <0.001) while the Spearman rank correlation is 0.975 ($p < 0.001$). Likewise, the ICC [3,2] is estimated at 0.979 (p <0.001), demonstrating high consistency in the positive sentiment proportions across the two versions of the annual reports. For negative sentiment, the Pearson correlation coefficient is 0.972 (p<0.001) and the Spearman rank correlation is 0.960 ($p <$ 0.001), indicating a strong association between the two documents. The ICC [3,2] for the negative sentiment category reached 0.986 (p<0.001). For the uncertainty sentiment, the analysis reveals that the Pearson correlation coefficient is 0.975 ($p < 0.001$) and the Spearman rank correlation coefficient for the uncertainty is 0.971 ($p < 0.001$). Moreover, the ICC [3,2] is estimated at 0.987 (p<0.001) for the uncertainty sentiment category across the two versions of the annual reports. A visual correspondence between the English original reports and their translated counterparts across all sentiment categories is presented in Figure 5.11.

The research further evaluates the impact of translation on sentiment in Arabic-English financial settings by applying a two-sided equivalence test following the approach of Blair and Cole (2002). The sentiment proportions identified in the original English annual reports and their machine-translated versions (from original Arabic) are statistically equivalent when the confidence intervals fall within the predefined equivalence margin of ± 0.25 standard deviations. Each sentiment category (positive, negative, and uncertainty) is measured as the proportion of sentiment words in that category to the total number of words in each document (without the stop words). As illustrated in Figure 5.8, the 90% confidence intervals for the three sentiment categories lie within the equivalence area, indicating that the sentiment proportions identified in the English reports are statistically equivalent to those in their translated versions.

Furthermore, sentiment preservation for the English annual reports (original and machine-translated) was evaluated based on tone at the document level. The overall sentiment tone was calculated as the difference between the positive and negative sentimental words, normalized by the total number of words in each report. Figure 5.9 displays the overall tone relationship between the original English annual reports and their machine-translated counterparts, indicating a high level of correspondence between the two versions of the report. The Pearson correlation coefficient is estimated at 0.940, while the Spearman correlation coefficient is estimated at 0.932, both statistically significant at $p < 0.001$.

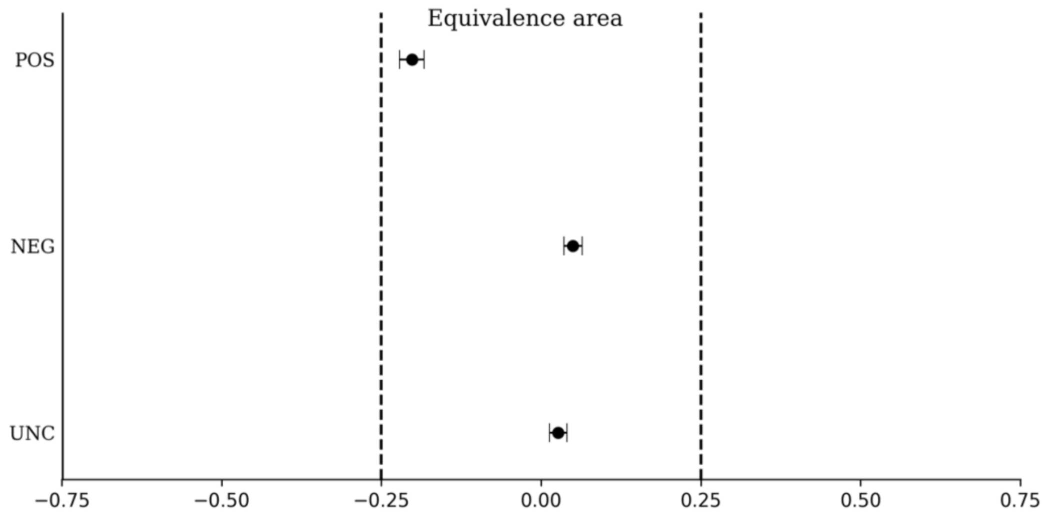

Figure 5-8. Two-sided equivalence test for the sentiment proportions between the original English annual reports and their English translations of the corresponding Arabic versions

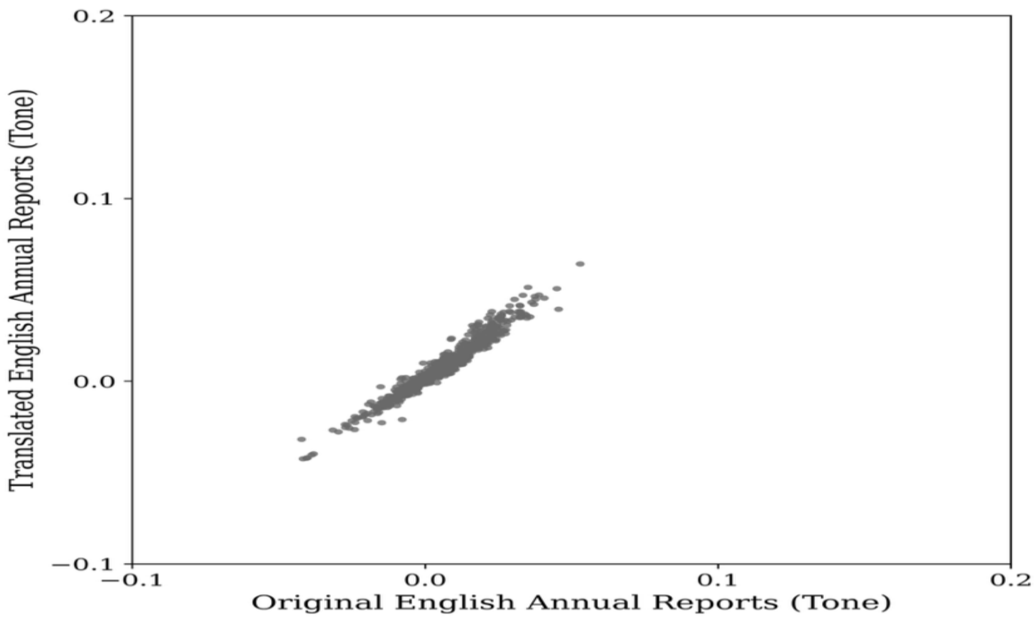

Figure 5-9. The overall sentiment (Tone) in the original English annual reports and their machine-translated English counterparts

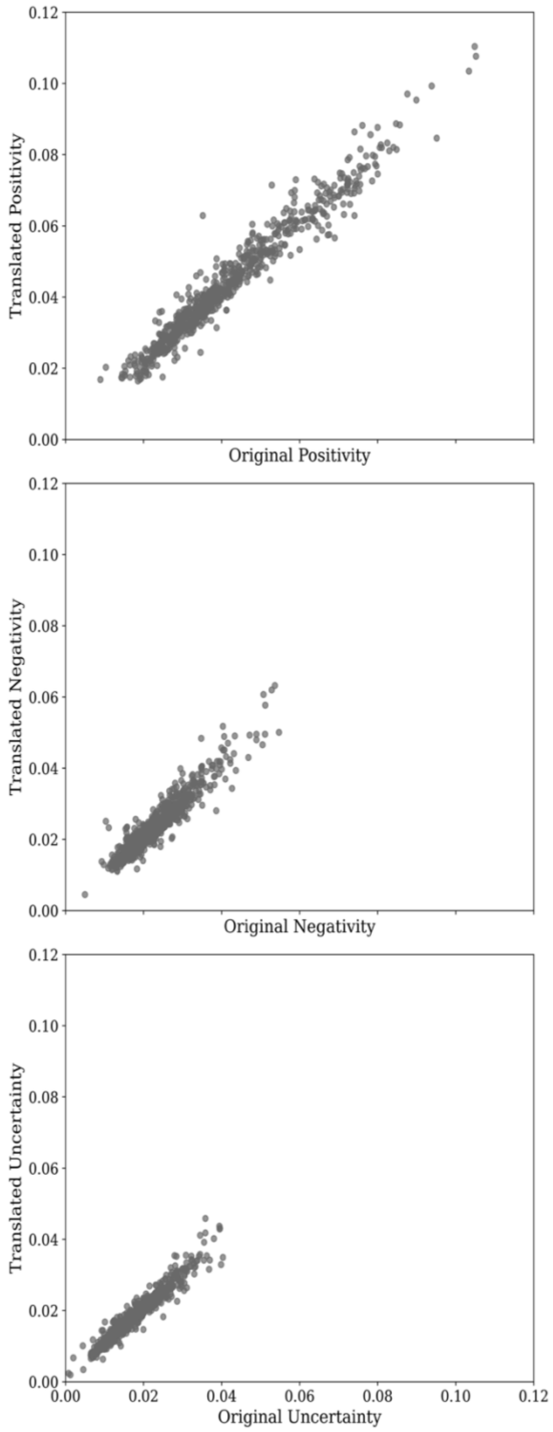

Figure 5-10. The relationship between original and translated sentiment proportions for positivity, negativity, and uncertainty in Arabic annual reports.

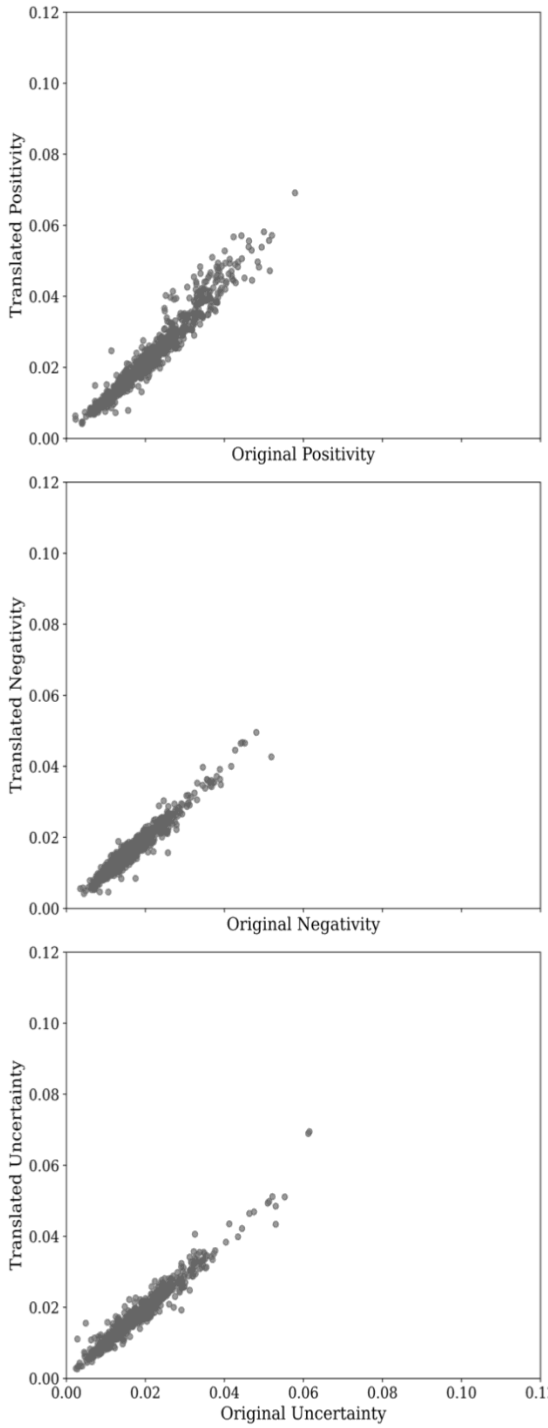

Figure 5-11. The relationship between original and translated sentiment proportions for positivity, negativity, and uncertainty in English annual reports.

5.6.6 Discussion of Sentiment Agreement in Financial Documents: Arabic and English Languages

The study employed a dictionary-based approach, correlation validation, and an equivalence assessment framework to determine the extent to which MT affects sentiment across the annual reports. The original annual reports, produced by Saudi public companies in both Arabic and English, are claimed to correspond to one another, reflecting each company's view of their performance and expectations for a given year. The analysis is conducted in a bidirectional assessment to observe any asymmetry that may arise from the translation. The experiment findings extend the CLSA and finance literature by validating MT systems for Arabic financial narratives. The translation impact assessment provides evidence of whether MT systems preserve the sentiment of the original financial disclosures. More importantly, if MT largely preserves textual sentiment, the findings are critical for further exploration of MT as a bridge for analyzing finance-domain text in low-resource languages.

The assessment of sentiment preservation in financial sentiment involves comparing sentiment words within each report's categories and comparing them to their counterparts. The agreement findings for the Arabic original annual reports and their machine-translated counterparts demonstrate a high level of sentiment preservation across all sentiment categories. As shown in the preceding sections, the correlation coefficients between the original Arabic reports and their Arabic translations from English documents exceed 0.9 across all sentiment categories. The results of the Pearson correlations are 0.0976 for positivity, 0.944 for negativity, and 0.966 for uncertainty, thereby indicating strong linear associations between the sentiment proportions across the two Arabic language versions. The Spearman's rank correlations also reflect similarly strong associations (0.976 for positive, 0.933 for negative, and 0.996 for uncertainty). Similarly, the ICC [3,2] demonstrates strong consistency across the sentiment categories (0.988 for positive, 0.970 for negative, and 0.983 for uncertainty). The two-sided equivalence test also confirms that the differences fit within the equivalence limits, implying that the MT variations are negligible. The categorical-level findings also align with the overall tone across the two versions of the Arabic reports, indicating a high degree of correlation.

To further assess whether MT distorts sentiment in the Arabic-to-English direction, the research compares the preservation of sentiment words across English annual reports. The results of the agreement analysis for the original English annual reports and their MT indicate strong preservation of sentiment across all categories. The correlational analysis reveals a strong relationship (greater than 0.96) between original English reports and their English counterpart translations. The Pearson correlation results demonstrate a strong linear relationship, with a correlation of 0.0969 for positivity, 0.972 for negativity, and 0.975 for uncertainty, thereby indicating consistent sentiment proportions across both English versions. Likewise, the Spearman rank correlations show similar strength levels: 0.975 for positive, 0.960 for negative, and 0.971 for uncertainty. Sentiment preservation across the English versions of the annual reports is also supported by the ICC [3,2]. Sentiment consistency across the proportion of sentimental words reached 0.986 for negative, 0.979 for positive, and 0.987 for uncertain, with all values statistically significant at the 1% level. The two-sided equivalence test also shows that the variances across the English versions are within the acceptable limits, indicating that the distortion of MT is minimal. These results are consistent with the overall tone of both English report versions, reflecting a strong correlation.

In Arabic, the analysis of annual reports and their translated counterparts reveals a high level of consistency across all sentiment categories. Despite the linguistic disparity between Arabic and English, the results suggest minimal distortion in sentiment due to MT. Although the findings reveal high consistency in sentiment preservation between the original Arabic annual reports and their machine-translated Arabic counterparts, there is a minor shift in positive sentiment across the Arabic datasets, with the translated annual reports showing fewer words identified (282,927 vs 274,791). Other sentiment categories exhibit similar distributions of words across the Arabic original and machine-translated reports (139,645 vs 140,272 in negative categories and 104,580 vs 104,001 in uncertain categories). Importantly, the proportion of sentiment at the categorical level across the original and translated Arabic reports remains highly correlated. Moreover, positive sentiment achieves the highest level of consistency with an ICC [3,2] of 0.988.

The structural and morphological complexity of Arabic is believed to pose significant challenges for the MT system in terms of accurately processing Arabic-English text. Nevertheless, the experiment's findings suggest that the MT system preserves the English-to-Arabic translation direction exceptionally well and, more importantly, that sentiment polarity and tone are not distorted during translation. The annual reports are formatted in MSA, a more standardized and structured form of Arabic than informal DA. Formal writing in communication, such as that in annual reports, reduces ambiguity and minimizes out-of-vocabulary issues, enabling the MT system to process the text more accurately.

To that end, Mohammad et al. (2016) encountered sentiment loss in their MT assessment (manually and automatically) on Arabic text. Because the authors evaluated sentiment preservation using social media blogging text, namely tweets, they found that MT systems often alter or lose the original sentiment. It is important to note that although Mohammad et al. (2016) evaluated sentiment loss after translation, they only assessed preservation by translating the text from Arabic to English. Moreover, the domain and style of text are expected to pose challenges, regardless of the translation direction. The authors found that sentiment words are often mistranslated into neutral terms, resulting in sentiment shifts from positive or negative to neutral. These observations are noted by the manual check validation applied by the authors. However, when the authors rely on the model classification output, they noted that the results are competitive compared to the original. More critically, the current analysis relies on a different domain and on more structured text. This is important because formal communication in annual reports does not typically contain sarcasm, metaphors, or incorrect word order, which were the main contributors to sentiment loss encountered by Mohammad et al. (2016). Therefore, the authors highlight that MT struggles to maintain the original sentiment in informal texts. Despite these limitations, the authors reached a conclusion that is consistent with the current research findings, confirming that MT of Arabic text into English yields competitive results.

Furthermore, the current analysis used Google Cloud Translation - Basic Model (v2) to translate the annual reports. Google utilizes NMT systems, which represent significant advances over previous traditional SMT methods (Stahlberg, 2020). The performance of the MT system is significantly influenced by the methodology used in its development. Furthermore, the assessment outcomes for sentiment preservation are expected to vary depending on the translation system used and its capabilities. Mohammad et al. (2016) employed an in-house translation system, a multi-stack phrase-based statistical MT, to translate the Arabic-annotated data into English. However, their experiment was conducted in 2016 and MT systems have since experienced significant advances. Consequently, the evaluation of sentiment preservation is affected by the performance of MT systems, which varies.

The research findings are consistent with prior Arabic translation assessments conducted using sentiment classification, indicating that sentiment is preserved through MT. Barhoumi et al. (2018) evaluated the impact of Arabic-English MT on sentiment classification using machine learning models. Their results indicate that sentiment analysis conducted on translated documents achieved competitive results, slightly better than those in Arabic, due to the English model’s capabilities. The authors attribute sentiment preservation to the advances in MT systems. However, in their assessment, the authors compared their results to those of Barhoumi et al. (2017), who also employed the same Arabic annotated dataset with stemming.

Barhoumi et al. (2018) suggest that Arabic may benefit from stemming, noting that Barhoumi et al. (2017) achieved a lower error rate of 23.31% after applying light stemming, compared to the 25.37% error rate obtained by the Arabic baseline in Barhoumi et al. (2018). Nonetheless, in dictionary-based sentiment analysis, the research confirms that stemming is less effective in accurately representing the word (see Appendix B.3 for further details).

In English annual reports, the direction effect in MT is more pronounced in Arabic-to-English translations at the word level. Although the findings indicate a high type-level match, the lexical set of the core sentiment words remains largely unchanged, although word frequencies reveal some differences. The positive sentiment words collectively increased by 19.6% in the Arabic-to-English direction. The translated annual reports show 140,095 positive words, whereas the original English reports show 117,137. Throughout the research's sentiment classification analysis, it has been observed that positive words are the dominant sentiment category across both the Arabic and English versions of the annual report, regardless of the sentiment dictionaries used. Notably, the number of predefined positive words is significantly lower than that of negative words according to the LM dictionary and the ArFinSD. The other sentiment categories, while they demonstrate moderate variations compared to the English-to-Arabic direction, display considerably less fluctuation than the positive proportions observed across the original and translated English annual reports.

Furthermore, across the bidirectional translation, the positive sentiment category demonstrates considerably greater variability than the negative and uncertainty categories. This is also observed in the English version of the CEO letters (7,556 in the original English CEO letters vs. 9,506 in the English-translated letters). To that note, the two-sided equivalence test for positive sentiment is marginally outside of the predefined area of equivalence. The increase in identified positive words may be attributed to the fact that various similar Arabic expressions correspond to more consolidated English terms, most of which are aligned with the LM dictionary. Mapping Arabic positive expressions to a single word increases the likelihood of being identified as positive. Ameur et al. (2020) noted that multiword phrases in Arabic often lack proper or direct equivalents, which poses challenges for MT systems. While word-level positivity identification varies between the original and translated English annual reports, the statistical evidence suggests that at the document level, the overall tone and proportion of categorical sentiment remain largely stable across the two versions.

In contrast to traditional MT Arabic assessment studies concerning quality and adequacy (e.g., Almahasees, 2021; Banimelhem & Amayreh, 2023; Habib et al., 2025), the current evaluation of translation employs a dictionary-based sentiment analysis approach to examine whether the two versions of the annual reports maintain the same tone. The findings of the current research indicate that shifts in sentiment categories and the overall tone remain negligible. The research's findings of a high degree of agreement between the original annual reports and their machine-translated counterparts suggest that MT systems can preserve sentiment in official financial communications. Notably, the standardized nature of annual reports tends to preserve sentiment after translation due to their formal and coherent writing style. Within the finance domain and dictionary-based approach, machine-translated Arabic documents exhibit high sentiment agreement with the original versions and, therefore, they may be suitable for CLSA or downstream sentiment classification. Furthermore, MT can enable the use of specialized sentiment analysis tools developed for high-resource languages in less-resourced languages.

5.7 Sentiment Analysis Results Limitations

Although this chapter provides valuable insights across the proposed sentiment analysis frameworks, several limitations must be acknowledged. First, the cross-language sentiment classification comparison, presented in Section 5.3, employed different NLP implementation approaches tailored to each language. The Arabic annual reports were based on lemmatized representations, whereas the English versions were based on the original surface words as they appeared in the extracted text. The results may be influenced by the normalization technique employed for the Arabic version of the annual reports, despite the effectiveness of the lemmatization approach in handling the Arabic morphological pattern. Therefore, the agreement in sentiment classification between the two versions must be interpreted with caution. Moreover, the research relies on the MLE disambiguation model (Obeid et al., 2020) to conduct the analysis. Although the NLP interpretation of the lemma is consistent, the performance and accuracy of lemmatization identification are inherently dependent on the model's capabilities. The results, therefore, may not be generalized across models or morphological disambiguators.

In addition, the research employs the large Arabic sentiment dictionary, ArSenL, to evaluate how effectively general dictionaries compare to ArFinSD in capturing the sentiment in financial narratives. The study, in Section 5.5, showed that the ArFinSD is more accurate at capturing sentiment in annual reports; however, the results cannot be generalized across all Arabic general dictionaries. Although the Arabic sentiment analysis literature emphasizes that specific domains require tailored dictionaries, sentiment dictionaries may perform differently when applied to financial-domain texts. To that end, ASA studies in finance are extremely limited, and there is no prior work assessing the accuracy of measuring tone in Arabic financial narratives using a general sentiment dictionary. Consequently, the research cannot draw definitive conclusions regarding the accuracy of general Arabic dictionaries in comparison to the ArFinSD.

Lastly, the research's findings on the MT effect on sentiment preservation in financial disclosures may be impacted by several factors. The evaluation is based on correlation analysis and statistical agreement tests, using the document-level categorical sentiment indices as a reference and a dictionary-based approach. The research relies on original annual reports for each language as the basis for comparison, with no gold-standard annotated reference text. Although the MT assessment can be evaluated through the sentiment analysis method (Mohammad et al., 2016), the absence of an annotated reference may limit the robustness of the evaluation. Additionally, the study cannot distinguish between sentiment shifts attributable to MT and those attributable to the firm's writing style in crafting the two versions of the annual reports. Also, the study assessed the MT's impact on the Arabic-English financial text by evaluating annual reports from Saudi-traded firms and employing the Google Cloud Translation Basic Model (v2). The study's findings should be interpreted with caution when other evaluation settings are considered.

5.8 Concluding Remarks

This chapter presents a comprehensive textual analysis of bilingual financial disclosures, offering a detailed examination of sentiment, dictionary performance, and translation equivalence across Arabic and English corporate narratives. It investigated the distribution and alignment of sentiment words across Arabic and English annual reports and CEO letters, comparing the performance of the developed ArFinSD with both the LM dictionary and the general-purpose ArSenL. Additionally, the chapter has empirically assessed the extent to which sentiment is preserved following MT of Arabic-English financial texts.

The first analysis compared the original financial disclosures using the ArFinSD and LM dictionary. The results showed that, despite morphological and structural differences between the Arabic and English languages, the two dictionaries consistently capture tone and sentiment at the document level. Additionally, the analysis was further extended to explore the negation effect across Arabic and English financial narratives, revealing that negation handling becomes critical in the Arabic language for improving sentiment classification.

The second analysis was designed to assess whether Arabic general sentiment dictionaries are capable of accurately gauging the tone in financial settings. The research carried out a comparative textual analysis across the ArFinSD and ArSenL to assess their ability to measure sentiment in annual reports and CEO letters. The analysis demonstrated that the Arabic finance-oriented dictionary, ArFinSD, is more accurate in gauging sentiment in financial narratives because it was established with a financial application in mind. The analysis reveals that the Arabic general dictionary, ArSenL, misclassifies words, leading to inaccurate tone assessments, and includes words (e.g., functional words) that do not carry sentimental weight in financial narratives, thereby undermining the managerial tone.

The third analysis provided insight into the MT of sentiment in financial narratives and whether sentiment is altered as a result. The analysis conducted a bidirectional MT impact assessment on the annual reports using the ArFinSD and LM dictionary. The research demonstrates that when using a dictionary-based approach and statistical validation methods, sentiment is largely preserved, confirming the findings of broad CLSA studies regarding the advancement of MT systems in preserving sentiment. Importantly, the findings open up avenues for exploring how financial markets respond to cross-linguistic variations in corporate disclosure communication. The findings may be beneficial for languages that lack specialized NLP resources in capturing the sentiment in financial narratives. Given the extensive evidence in the finance literature that sentiment analysis in financial narratives requires appropriate tools, MT systems may provide a valuable bridge to overcome these limitations.

After establishing the reliability of the ArFinSD in cross-language comparison settings and in comparison with a general Arabic sentiment dictionary, the next chapter advances the analysis from linguistic settings to empirical financial testing, investigating whether sentiment tone derived from annual reports in both languages is associated with observable market reactions around the disclosure event. The study will utilize the finance-oriented dictionaries, the ArFinSD and the LM dictionary, to examine whether the SSE market responds differently to the bilingual tone in the annual reports.

Chapter 6. Market Reaction to Bilingual Tone on the Saudi Stock Exchange

6.1 Introduction

Having established the linguistic validity of the research's proposed Arabic Financial Sentiment Dictionary (ArFinSD) in the preceding chapter, this chapter extends the analysis by applying the dictionary to assess whether the bilingual tone in the annual reports is associated with market reaction in the Saudi Arabian capital market. This chapter aims to answer the research question: *To what extent does the Saudi Stock Exchange respond differently to textual sentiment in the Arabic and English annual reports?* Chapter 5, Section 5.3, provides evidence that the ArFinSD yields sentiment classification results comparable to those of the LM at the document level, while exhibiting some asymmetry across two versions of the annual report. This chapter assesses how such linguistic differences may translate into observable market reactions in the Saudi Stock Exchange (SSE). Additionally, as Loughran and McDonald (2011) observe, "*one way to test word lists is to examine the market's reaction at the time of 10-K filing*." The research demonstrates that Arabic financial narratives require specialized tools to capture tone accurately, and a general Arabic dictionary often misclassifies sentiment and introduces noise into the measurement. This chapter provides appropriate empirical settings for evaluating the practical performance of ArFinSD in explaining market reactions.

The chapter transitions from the linguistic dimension to the market dimension to examine the bilingual tone within the SSE. The chapter examines how the bilingual tone relates to subsequent market reactions and whether the two versions differ in informativeness. Specifically, it investigates whether sentiment measures derived from Arabic annual reports (using the ArFinSD) and their English counterparts (using the LM dictionary) are reflected in observable market reactions around the filing of these reports in the SSE. The chapter also provides new insights into bilingual corporate disclosure, which prior work has primarily examined the tone in a single language (predominantly English).

A distinctive feature of SSE is the requirement to disclose annual reports in both Arabic and English. In recent years, Saudi Arabia has undertaken substantial economic and regulatory reforms, with the capital market legislative bodies continuously enhancing corporate practices. Additionally, with the introduction of Vision 2030, Saudi Arabia aims to become a leading global financial hub, attracting foreign investments. Therefore, the bilingual corporate reporting environment becomes particularly important to examine. The chapter examines whether the sentiment conveyed in Arabic and English annual reports, as measured using language-appropriate sentiment dictionaries, is associated with market reactions to the disclosure. More importantly, it further examines whether the market reaction to the annual reports differs across the two languages.

The research employs an event study methodology to assess whether negative, positive, and uncertainty sentiment extracted from Arabic annual reports and their corresponding English versions is associated with cumulative abnormal returns (CARs) around the disclosure release date. The event study aims to determine whether corporate events, such as the publication of annual reports, result in abnormal or excess returns that differ from those expected under normal market conditions. The event study approach is one of the most widely used methods for evaluating market reactions to events (Ball & Brown, 1968; Brown & Warner, 1980; Fama et al., 1969), providing empirical settings in which textual sentiment can be assessed.

The chapter is structured as follows. Section 6.2 describes the Saudi economy and its stock exchange market. Section 6.3 discusses the development of hypotheses on textual sentiment in corporate disclosures and bilingual tone. Section 6.4 presents the methodological framework and study design. Section 6.5 presents the study results, beginning with descriptive statistics and proceeding to empirical results and discussion. Lastly, the Chapter discusses the study's limitations in Section 6.6 and concludes with final remarks in Section 6.7.

6.2 The Saudi Financial Market

Today, the Kingdom of Saudi Arabia stands as the largest economy in the Middle East and North Africa (MENA) region, with a GDP of approximately USD 1.24 trillion as of 2024 (World Bank, n.d.). Its stock exchange, the Saudi Exchange, is also the largest capital market, accounting for more than two-thirds of the total market capitalization of the MENA region, and it is regarded as one of the ten largest markets worldwide in terms of market capitalization (Alshammari & Goto, 2022; Bajaher et al., 2022).

Driven by the government's objective of reducing its overreliance on the oil sector and diversifying its economy, and by deficiencies stemming from the 2006 Saudi stock market crash, a substantial reform of the capital market was initiated in 2007 (Alsuhaibani et al., 2023). The 2006 market crash set a precedent in the history of the SSE, established in 1985, as the market lost approximately 65% of its value by the end of that year. The lack of adequate market infrastructure is believed to be the primary contributor, among others (for further details on the 2006 Saudi market crisis, see Lerner et al., 2017; Alkhaldi, 2015). The infrastructure reforms are led by the Capital Market Authority (CMA), the sole financial regulator of Saudi Arabia's capital market, to promote investment, transparency, and disclosure standards across listed companies. Since then, the CMA has consistently monitored the market, ensuring fair practices and high standards of corporate governance compliance.

Furthermore, in 2016, the Kingdom of Saudi Arabia announced its 2030 Vision, which is assembled around three themes: a vibrant society, a thriving economy, and an ambitious nation (Vision 2030, 2025a). Two objectives of the 2030 Vision are to increase foreign direct investment and to position the Kingdom as a hub for global investment. These objectives are set to be achieved through various channels. For example, to promote financial market liberalization, the CMA relaxed registration requirements and expanded the eligibility of foreign institutional investors. This was achieved by easing the Qualified Foreign Investor (QFI) program requirements, which were initially introduced in 2015 and were considered a milestone, thereby enabling international institutional investors to hold shares directly on the Saudi Stock Exchange. Additionally, as part of Vision 2030, the Financial Sector Development Program (FSDP) was launched in 2018 to transform Saudi Arabia into a globally integrated financial hub. The program encompasses multiple sub-sectors and key financial-sector regulators, aiming to align the country's financial sector with the highest international standards and to position the domestic capital market as a leading global financial hub (Vision 2030, 2025b).

These programs have strengthened the market's governance framework and transparency standards, increasing its international exposure. For example, in 2019, SSE and Morgan Stanley Capital International (MSCI) finalized the inclusion of the Saudi Stock Exchange market in the MSCI Emerging Market Index. Similarly, in the same year, SSE completed the process to join other global equity indices, including the Financial Times Stock Exchange (FTSE Russell) and the S&P Dow Jones Index (S&P DJI). The inclusion of the Saudi Exchange in global emerging-market indices is intended to attract foreign investors. According to Bajaher et al. (2022), these steps played a critical role in attracting a substantial number of Qualified Foreign Investors in 2019, with the total number nearly quadrupling from 500 to 1,800 throughout that year. The inclusion of major global emerging-market indices in 2019 significantly boosted foreign investors' activity, resulting in a 309% rise in QFI registrations, a 665% surge in QFI holdings, and a 558% increase in their contribution to total traded value. The increase in the number of Qualified Foreign Investors is also linked to the largest IPO in history. In 2019, Aramco, the world's largest crude oil exporter, was listed on the Saudi Stock Exchange. The Aramco listing boosted market liquidity and attracted new foreign investment portfolios through the QFI program.

These policy initiatives and market infrastructure reforms have resulted in substantial expansion of the Saudi exchange market, with the number of listed companies rising from 75 in the early 2000s to 199 by 2019 and further increasing to over 260 by 2025. Over the same period, market capitalization surged from USD 68 billion in 2000 to more than USD 2.4 trillion by 2019, reaching approximately USD 2.6 trillion by the first quarter of 2025 (Saudi Exchange, n.d.). The QFI program participants continued to show rapid growth over recent years, reaching 4,181 by the end of 2024, with total holdings of approximately USD 90 billion (Saudi Tadawul Group, 2024). Figure 6.1 illustrates the development of the QFI program from 2019 to 2024. The significant growth reflects the efforts of post-2006 market infrastructure reforms implemented by market regulators and the Vision 2030 initiatives, which aim to transform SSE into one of the world's most attractive capital markets.

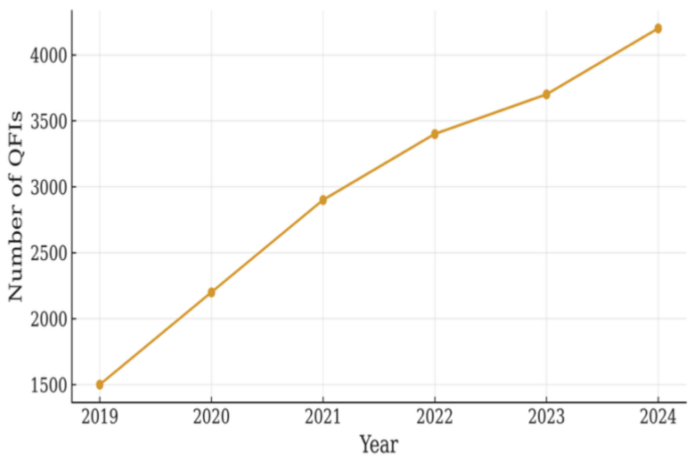

Figure 6-1 Growth of Qualified Foreign Investors (QFIs) in the Saudi Stock Exchange (2019-2024)-adapted from the Saudi Tadawul Group Report (2024).

The Saudi Stock Exchange comprises 23 industry sectors, reflecting the diversity of Saudi economic activities listed on the exchange (see Table 6.1). These sectors reflect core industries such as Energy, Basic Materials, and Financials (including Banks, Insurance, and diversified Financial Services). The Basic Materials and Banking sectors are the most significant components of the Saudi Market index, accounting for approximately 16.9% and 16.6% of the total market capitalization, respectively. The Energy sector ranks third, accounting for approximately 9%[30], while Telecommunication Services, Insurance, and Real Estate each account for between 4% and 6%. Other sectors, including Pharmaceuticals, Media and

[30] Aramco is excluded from the market capitalization summary. It represents approximately 70% of the total market capitalization.

Entertainment, Capital Goods, and Real Estate Investment Trusts, collectively account for less than 2% of total market capitalization. The SSE exhibits concentration in a few dominant industries while gradually expanding into a broader, more balanced market. In 2024, the Saudi exchange recorded 44 new listings across a wide spectrum of sectors, demonstrating both increased corporate participation and ongoing diversification of listed industries.

Table 6.1 Saudi Stock Exchange Market Structure by Industry Group

#	Industry Group	#	Industry Group
1	Banks	13	Household & Personal Products
2	Capital Goods	14	Insurance
3	Commercial & Professional Svc	15	Materials
4	Consumer Discretionary Distribution & Retail	16	Media and Entertainment
5	Consumer Durables & Apparel	17	Pharma & Biotech & Life Science
6	Consumer Services	18	REITs
7	Consumer Staples Distribution & Retail	19	Real Estate Mgmt & Dev’t
8	Energy	20	Software & Services
9	Financial Services	21	Telecommunication Services
10	Food & Beverages	22	Transportation
11	Health Care Equipment & Svc	23	Utilities

Source: The Market Data Premium Reports Database (MDPRD), Tadawul Listed Equity Master Data Report, https://ereference.tadawul.com.sa/

Despite a significant increase in foreign investment participation, the SSE continues to be predominantly dominated by retail investors. According to the CMA (2020), approximately 86% of daily market transactions are driven by non-institutional investors, compared with 14% by institutional investors. The SSE classifies individuals into four categories, including ordinary retail investors, high-net-worth investors, individual professional investors, and individual portfolio managers. More importantly, more than 50% of daily trading volume is attributable to retail investors who are neither experienced nor wealthy (Alshammari & Goto, 2022). Yet, the majority of listed equity is owned by institutional and government entities.

The Saudi Stock Exchange has seen notable improvements in the disclosure environment, driven by legislative requirements imposed on listed companies. The CMA oversees all public disclosures, including annual reports, announcements, and quarterly reports. For example, the CMA sets strict disclosure requirements for all listed firms and establishes mandatory timelines for financial reporting, with due dates of 30 days for quarterly statements and 90 days for annual reports. Among all corporate disclosures, the annual report is regarded as the most comprehensive. It is the report in which narrative financial information accounts for a significant volume of the disclosure, compared with other disclosures, such as quarterly and annual financial reports. Companies have the discretion to expand or limit the extent of information shared with the public to the mandatory components. Other corporate disclosures, such as financial reports, are strictly regulated by accounting standards, particularly the International Financial Reporting Standards (IFRS). Several studies have examined the level or quality of information disclosed within the annual reports of listed companies on the SSE (Alsaeed, 2006; Naser & Nuseibeh, 2003; Al-Moataz & Hussainey, 2012; Al-Janadi et al., 2013).

The SSE offers an ideal setting for evaluating the role of tone and sentiment across bilingual communication channels, as reflected in annual reports, and for determining whether tone has explanatory power in shaping returns within the SSE. With the recent effort to liberalize the SSE and the growth in foreign investor participation, firms' practices are expected to improve, leading to higher-quality disclosures. As discussed in Bae et al. (2006), foreign investors demand transparency, stricter disclosure rules, and compliance with corporate governance standards. Therefore, the tone and sentiment conveyed in the Arabic annual reports and their English counterparts present a critical dimension of the information environment in the SSE. Evaluating how textual sentiment affects market responses provides valuable insights into how soft information translates into observable market reactions.

Furthermore, in light of the ongoing transformation of the Saudi economy under Vision 2030, corporate transparency and the quality of information released by listed firms have become increasingly significant areas for examination. The SSE has undergone substantial regulatory and institutional reforms since the 2006 market crash, including the introduction of various disclosure governance standards. These regulations are implemented to enhance transparency, making corporate communications more relevant to market participants. In markets with a strict governance framework that emphasizes clarity and timely disclosures, the tone conveyed in corporate narratives is more likely to be reflected in prices. However, as discussed earlier, managers have greater power over narrative content than over quantitative information, which is strictly regulated by accounting standards. Therefore, the tone in annual reports may reveal information not reflected in quantitative data.

As demonstrated in Chapter 5, Section 5.3, the ArFinSD yields more accurate results than Arabic general sentiment dictionaries. The research findings presented in Chapter 5 suggest that assessing sentiment in financial Arabic narratives requires a specialized dictionary, as general dictionaries are often prone to misclassifying tone in corporate disclosures. The SSE provides the appropriate setting to examine the ArFinSD's ability to gauge sentiment and determine whether tone has explanatory power in the SSE market. By applying the ArFinSD, the research provides further empirical evidence of the dictionary's effectiveness in accurately capturing the sentiment in Arabic financial narratives. It also demonstrates its value in enhancing textual sentiment analysis in Arabic corporate reporting narratives, where word polysemy is a critical issue. Although the content of corporate disclosures issued by Saudi-traded firms has been investigated in several studies, the examination of tone in annual reports in a cross-language setting remains unexplored. To the best of the researcher's knowledge, no study has examined the market reaction to the textual sentiment of corporate disclosures within an Arabic-English cross-lingual context.

6.3 Textual Tone, Bilingual Reporting, and Market Reaction: Hypotheses Development

A substantial body of literature in finance and accounting investigates the tone of the annual report, or of its components, and its associations with market reactions around the disclosure release. Loughran and McDonald (2011) find that firms whose annual reports contain higher proportions of negative and uncertain words experience fewer excess returns following the report's release. The authors, by contrast, find that positive sentiment is not associated with observable market reactions. The authors did not find a clear pattern with filing returns when gauging the tone of the MD&A section. Following the approach of Loughran and McDonald (2011), Bannier et al. (2019) apply their German version of the LM dictionary to measure market reactions to both the quarterly and annual reports. Their evidence suggests that tone is statistically associated with excess market returns in quarterly reports, indicating that reports with fewer negative and uncertain words, or more positive words, are related to subsequent excess returns. However, the authors find no statistically significant association between sentiment in annual reports and excess returns, arguing that nearly half of German companies release preliminary annual results reports that capture and absorb most of the market reaction.

Other empirical evidence suggests different associations between tone and corporate disclosures. Yekini et al. (2016) examine positivity in UK companies' annual reports using Henry's (2008) wordlist and find that a positive tone is associated with higher returns. In contrast, when the authors consider Henry's (2008) negative word list, they find that the negative tone is not statistically significant. Jegadeesh & Wu (2013) find that both positive and negative sentiment words, as defined by the LM dictionary, are statistically associated with market returns up to 2 weeks after the release of 10-K reports. Their results suggest that the market may incorporate soft information gradually rather than immediately. Similarly, Feldman et al. (2010) employed the LM positive and negative wordlists to examine the short-term market reaction to changes in MD&A tone in a sample of annual and quarterly reports. The authors found that a managerial tone that becomes incrementally more positive or negative is associated with an immediate market reaction. Collectively, these studies provide evidence that textual sentiment in firms' disclosures can influence returns, even though the role of each sentiment category varies across markets.

While prior research finds that positive tone is associated with a short market reaction, others question whether it is as informative as negative tone. Huang et al. (2014) suggest that positive tone may serve different roles, including reflecting genuine financial performance, serving as managerial signaling of private information constrained by accounting standards, or representing strategic obfuscation to conceal anticipated poor performance. Loughran and McDonald (2011) showed that a positive tone does not have predictive power for explaining excess returns. By contrast, a negative tone tends to have a more consistent and pronounced effect on returns. Tetlock et al. (2008) emphasize that the predominance of negative sentiment aligns with extensive prior research in psychology (e.g., Rozin & Royzman, 2001; Baumeister et al., 2001), which suggests that negative information has greater influence and is processed more thoroughly than positive information.

Although the finance literature has primarily focused on negative or positive managerial tone, uncertainty tone plays a critical role in explaining market reactions. Loughran and McDonald (2011) investigate the predictive power of uncertainty and find that uncertain language in the 10-K reports is associated with a negative market reaction in the event window around the filing date. Loughran and McDonald (2013) find that uncertainty language in S-1 filings is associated with higher first-day returns for IPOs and increased return volatility. Despite evidence linking uncertainty to abnormal returns, some argue that uncertainty does not signal a definitive positive or negative effect and may not prompt an immediate market response reflected in abnormal returns. Therefore, studies, such as Black et al. (2025), suggest that uncertainty language in corporate disclosures can be interpreted as a risk signal of information asymmetry or ambiguity, thereby affecting market trading behavior.

Evidence from the existing literature suggests that negative, positive, and uncertainty can be informative in explaining stock returns. However, the degree to which each category affects the market varies across sentiment categories and across studies. A negative tone has been consistently shown to be associated with lower returns following the release of disclosures. The optimistic tone often shows a less pronounced and less consistent influence on returns. Likewise, uncertainty creates ambiguity and risk factors across investors rather than a clear direction. Yet, some evidence suggests it is negatively associated with short-term market returns. Mixed evidence regarding the role of each sentiment category motivates an examination of the tone of market reactions on the SSE, where listed firms are mandated to produce bilingual annual reports. Since the research developed an Arabic finance-oriented dictionary, ArFinSD, the study applies it alongside the LM dictionary to examine the role of tone in the SSE's bilingual environment.

The SSE, as outlined in section 6.2, has experienced a notable increase in foreign investor participation, which requires higher standards of compliance, transparency, and accuracy in the bilingual reporting environment. The annual report serves as a valuable vehicle for communication, attracting potential investors and retaining current stakeholders. Managers may use annual reports opportunistically, since several narrative components of the report are less regulated than other sections, such as financial statements, which are strictly regulated by market authorities or IFRS. Companies carefully craft the language and tone of narrative sections in annual reports, strategically shaping these messages to meet their objectives. According to the CMA's regulatory guidance, the Arabic version of the corporate disclosure carries legal weight. For the large majority of firms in the SSE, the annual reports explicitly state that, in the event of any discrepancy between the two versions, the Arabic version prevails. Given the growing importance of bilingual reporting as the SSE positions itself as a lucrative capital market for the international audience, the study provides insights into how the tone identified across both languages translates into market reactions.

Although empirical studies directly linking bilingual disclosures to market reactions are relatively scarce, a growing body of literature has examined bilingual corporate reporting from various perspectives. Recent evidence from the Hong Kong market (Do et al., 2025) indicates that sentiment in Chinese annual reports is informative for investors, whereas sentiment in English reports is not. Their evidence suggests that abnormal sentiment in the local-language annual reports is associated with CARs. In contrast, the counterpart sentiment measure in the English version shows no significant association with market reaction. Moreno (2024) examined impression management in chairpersons' statements in bilingual annual reports, using LIWC to analyze textual characteristics, including first-person pronouns, tone, and certainty. The author found no significant differences in impression management between the two language versions and concluded that investors may read either version. Leventis and Weetman (2004) compared voluntary disclosure practices between Greek companies that publish annual reports in the local language and those that adopt bilingual reporting. Companies that provided both English and Greek versions were found to disclose more information and strategically appeal to international audiences. Bao and Wei (2024) find that

Chinese firms that issue ESG reports in both Chinese and English attract greater participation from foreign investors. These studies indicate that language matters and it reflects how information is conveyed and interpreted, especially from a foreign investor's perspective.

Bringing together the evidence outlined above and the SSE bilingual environment, the study examines whether the textual sentiment as identified in the LM and ArFinSD dictionaries, including positive, negative, and uncertain, helps to explain abnormal returns after the release of annual reports. More importantly, the study examines the extent of the market reaction to tone across the Arabic and English annual reports and whether this reaction differs. Based on prior research on the role of textual sentiment, a more negative and uncertain tone is expected to be associated with a negative market reaction. In contrast, a positive tone is expected to be related to a positive market reaction. Additionally, the study aims to determine whether the SSE responds differently to sentiment across languages; these expectations are formulated separately for the Arabic and English tone indicators. The study proceeds to test the following hypotheses:

H1a: A higher negative tone in the Arabic annual reports is associated with lower abnormal returns around the filing release day.
H1b: A higher negative tone in the English annual reports is associated with lower abnormal returns around the filing release day.

H2a: A higher positive tone in the Arabic annual reports is associated with higher abnormal returns around the filing release day.
H2b: A higher positive tone in the English annual reports is associated with higher abnormal returns around the filing release day.

H3a: A higher uncertainty tone in the Arabic annual reports is associated with lower abnormal returns around the filing release day.
H3b: A higher uncertainty tone in the English annual reports is associated with lower abnormal returns around the filing release day.

6.4 Methodological Framework and Study Design

Inspired by the work of Loughran and McDonald (2011), who first developed and then examined the association between their proposed dictionaries and market reactions, the study adopts a similar empirical framework. The authors employed an event-study framework and evaluated their word lists by examining the association between tone and excess returns around the 10-K filing for each proposed word list. Their motivation was based on whether dictionaries developed for sociology and psychology are appropriate for business narratives. Building on this foundation, the current study applies a similar approach, using finance-oriented dictionaries, to examine whether tone identified in annual reports across both Arabic and English is associated with market reactions. By adapting this framework to SSE bilingual reporting settings, the analysis aims to examine the extent of market reactions to these sentiment measures around the filing of the annual report, thereby testing the hypotheses established in the processing section.

Within this framework, the chapter addresses the following question: *To what extent does the Saudi Stock Exchange respond differently to textual sentiment in Arabic and English annual reports?* To empirically explore the question, the study employs an event study methodology and utilizes the financial textual datasets established in this research, enabling an empirical assessment across two versions of the report: Arabic annual reports measured using ArFinSD and English reports measured using the LM dictionary, as outlined in Chapter 5, Section 5.3. The availability of both Arabic and English annual reports enables an empirical evaluation of whether the sentiment expressed in each language provokes observable market reactions. To accomplish this, the research relies on three sentiment categories, including positive, negative, and uncertainty, established using the ArFinSD and LM dictionaries.

The assessment aims to evaluate whether the narrative tone conveyed in Arabic and English reports has explanatory power within the context of the SSE market, and to what extent the market responds to the sentiment expressed in each report. The bilingual study design is similar to that of Do et al. (2025), who investigated the bilingual tone responses in the Hong Kong market using LIWC and abnormal sentiment measures. In contrast, the current analysis differs in that it uses the ArFinSD and LM dictionaries to identify the textual sentiment and employs the proportion of sentiment words as the tone measure. In the SSE market, Arabic is recognized as the legal and official language, making it the primary reference for domestic investors and legislative bodies. In contrast, English annual reports are used to inform foreign and international investors regarding the firm's performance and trajectory. However, the research, in the processing chapter, demonstrates linguistic asymmetry in the sentiment conveyed in annual reports, which may be attributable to differences in authorship and communication styles across the two languages. The analysis, therefore, advances the comparison of bilingual reporting by examining how these linguistic differences translate into market outcomes.

6.4.1 Event Study

Event studies have become an essential methodology in empirical finance for assessing how specific economic events influence firm value. By considering the principle that new information influences asset prices, event study research examines abnormal returns around public announcements to gauge how the market responds (Ball & Brown, 1968; Brown & Warner, 1980; Fama et al., 1969). The event study methodology has evolved since its emergence in the United States over three decades ago (Nobanee et al., 2009) and remains an essential method for assessing corporate disclosures and other events in financial markets.

The research employs an event study methodology to assess how sentiment conveyed in annual report disclosures influences cumulative abnormal returns around the report release date. Cumulative abnormal return (CAR) is widely used as the standard measure of market reaction to firm-specific events (Brown & Warner, 1985; Mackinlay, 1997), including annual reports (Griffin, 2003). Despite some minor methodological improvements over time, the fundamental approach remains the same: measuring actual returns relative to expected (benchmark) returns around the event day under study. The divergence indicates that the market has reacted to the event. Abnormal returns can be estimated using various methodological approaches, including market-adjusted returns, mean-adjusted returns, CAPM-based returns, market-model returns, and the Fama-French three-factor model.

The fundamental setup of the event study involves a regression analysis in which the dependent variable is the abnormal stock market return around the event time (Henry, 2008). Event studies and abnormal returns have been widely employed in prior research to examine the market's reaction to different textual sentiment measures. Beyond textual sentiment analysis, several studies have applied event methodology to examine different events in the SSE, including insider trading (Alqurayn et al., 2024), the COVID-19 pandemic (Sayed & Eledum, 2023), and political events (Fodol & Aziz, 2019).

6.4.2 Event Day

The research defines the event day (t=0) as the release of the annual report, on which the market incorporates information from the disclosures. Following the standard event study methodology (Brown & Warner, 1985; Mackinlay, 1997), the event day corresponds to the official filing date of the annual report's public release. However, firms listed on the Saudi Exchange have the discretion to file their annual reports outside trading hours, including weekends and market holidays. The annual reports and financial reports are excluded from the requirement to be disclosed during market trading hours.

To address the release of the annual reports on non-trading days, the study follows prior research (Berkman & Truong, 2009; Sorokina et al., 2013) by adjusting the event day (t=0) on a non-trading day to the next available trading day based on the market's official trading calendar. Adjusting for non-trading days is a commonly used approach in event research, especially in cross-country market studies. To establish a consistent event day, the research defines the event day (t=0) using the following rule:

1. Trading day disclosure release: The event day is established if the firm publishes its annual report on a trading day, according to the SSE calendar.
2. Non-trading day disclosure release: The event day on non-trading releases is defined as the first subsequent trading day, according to the SSE calendar.

6.4.3 Event Window

The event window is critical when examining the subsequent market reaction to the event under study. The research objectives, market characteristics, and the nature of the event under study strongly influence the selection of the appropriate event window. Previous studies in developed markets, especially those analyzing 10-K filings in the U.S., use relatively short event windows to capture the immediate market reactions around the filing date. Griffin (2003), for instance, finds that the market response to 10-K filings is elevated on the day of filing and during the immediately following days. Similarly, Loughran and McDonald (2011) adopt the [0, +3] event window to examine the market reaction to textual sentiment. In addition, Henry (2008) employs CAR [−1, +1] to capture immediate market reactions, although the study examines the market reaction to tone in earnings press releases. The short event window provides a critical benchmark for examining the immediate market reaction to textual information in corporate disclosures. Nonetheless, Event study methodology requires context-specific selection rather than a universal standard. Mackinlay (1997) argues that markets must be given sufficient time to respond to events fully, and the length of the window depends on market and event characteristics.

The research considers short (CAR [−1, +1]), medium (CAR [−1, +5]), and long (CAR [−1, +10]) windows to observe market reactions to sentiment in Arabic and English annual reports, using the ArFinSD and LM dictionaries, respectively. The selection of these three event windows allows the research to examine market reactions at different stages after the release of the annual reports. CAR [−1, +1] captures the immediate market response around the annual report filing date. CAR [−1, +5] extends the post-filing period to five trading days, or one trading week, to examine whether the information conveyed in the annual reports continues to be incorporated into market prices. CAR [−1, +10] further extends the post-filing period to ten trading days, or two trading weeks, to examine whether the association between tone and returns develops or persists over a longer period. Since all event windows start at day -1, they provide a consistent basis for comparing the immediate, medium, and longer market reaction to textual sentiment in the SSE.

Several studies have adopted a multi-window approach to capture market reaction to tone over different horizons. For example, Azimi and Agrawal (2021) examine the immediate market reaction to 10-K sentiment and then assess whether the relationship continues or reverses over the subsequent one week, two weeks, and one month after the filing period. Their multi-event window design of one and two trading weeks is similar to the research's event window selections of the five- and ten-trading-day windows. Similarly, Angelo et al. (2025) examine the market reaction to tone using CAR [−1, +1], CAR [−1, +2], and CAR [−1, +5] to capture the immediate and delayed market reaction to earnings announcements. Therefore, prior financial textual analysis research supports using a multi-event window rather than limiting the examination of managerial tone to the immediate filing period.

The multi-event window approach also aligns with the study's aims and objectives. The annual report inherently presents considerable informational complexity, which may require a longer processing time. Loughran and McDonald (2011) note that the median 10-K contains approximately 20,000 words, and the average investor may require longer time to process disclosure information. This suggests that the association between tone and returns may not be fully captured in the short period after release. The authors also examine shorter filing windows and find that when the event window is reduced to [0, +2], only some sentiment indicators show predictive power, while sentiment indicators fail to capture market reactions over the [0, +1] window. This indicates that a very short event window may fail to capture the association between tone and market returns. Similarly, You and Zhang (2009) examine the immediate and delayed market reaction to 10-K information and find that return volatility does not appear to return to its pre-filing level even ten trading days after the filing. The authors note that investor underreaction is stronger for firms with more complex 10-K reports, suggesting that the information conveyed in 10-K reports may take longer to be incorporated into prices. Miller (2010) also shows that more complex, longer, and less readable 10-K reports are associated with lower trading activity, particularly among smaller investors. These studies emphasize the complexity of annual reports and the time required to process their content. Therefore, extending the event window to one- and two-trading-week periods allows the research to observe whether the association between textual sentiment and returns develops beyond the immediate filing period.

The research's multi-window design is also supported by prior evidence from the SSE. Alzahrani and Skerratt (2010) examine market reactions to earnings announcements for Saudi-traded firms over the immediate announcement period and subsequent post-announcement weeks. The authors note that price adjustment can continue beyond the immediate announcement period. Alzahrani (2010) examines the post-announcement returns over extended periods, including one, two, three, and four weeks. The one- and two-week trading windows provide a relevant market precedent for evaluating market reactions over progressively longer windows. Syed and Bajwa (2018) also examine market reactions to earnings announcements over an event period extending ten trading days after the announcement and provide evidence of significant abnormal returns. Although these studies examine earnings announcements rather than the tone in annual reports, they provide relevant evidence that Saudi market responses to financial information may emerge or develop beyond the immediate event period. This provides market-specific support for examining market reactions over short, medium, and long windows, rather than relying on a single narrow window.

In addition, the study assesses the bilingual reporting environment at the SSE, employing the ArFinSD to gauge sentiment in Arabic reports and the LM to gauge sentiment in the corresponding English reports. The two dictionaries may identify distinct sentiment words, as each measures the sentiment from a particular linguistic source. Therefore, the observable market reaction may differ accordingly. Applying a consistent multi-event window to both language versions is critical for assessing how the market reacts to sentiment indicators across the two versions of the annual report, using the ArFinSD and LM dictionaries. More importantly, by adopting the same short, medium, and long event windows, the research can assess whether any observable association with textual sentiment appears immediately or develops over the medium and long windows for each language.

6.4.4 Data and Sample Selection

The study relies on the official Saudi Stock Exchange (Tadawul) website[31], which provides direct access to disclosures from listed companies. Each firm's annual reports, in both Arabic and English, were obtained individually using the company profile pages, where Tadawul maintains an authoritative timestamp for each report's official publication date. This is critical to ensure that all annual reports in the study are both accurate and consistent. These reports are initially extracted in the textual analysis phase of this research (see Chapter 4, Table 4.1). Additionally, firm-level financial data employed in the analysis are obtained from the Bloomberg Terminal. The study also relies on the Market Data Premium Reports Database (MDPRD)[32], a component of the Tadawul E-Reference Data System. The system's platform provides extensive information on the SSE, including historical data, publications, announcements, and news, among other disclosures. The study utilizes MDPRD to obtain the firm- and market-level daily trading data. The data are organized as open, low, high, and close, along with daily trading value and volume. The research employs textual data from the annual reports in both languages, as presented in Chapter 5, Section 5.3, and cross-references these data with market- and firm-level financial data. To meet the study objectives, the research applies the following criteria for selecting a firm and its corresponding annual:

1. **Stock Exchange Listing:**
   Firms must be listed on the Stock Exchange during the study period. The research excludes firms that are delisted or merged.
2. **Minimum Trading Activity:**
   Firms must have traded for at least 90 days prior to the release of their annual reports, excluding newly listed firms.
3. **Financial Data Availability:**
   Firms must have non-missing trading prices during the event window. In addition, the financial variables used in the analysis must be non-missing. The research excludes observations for which financial data are missing.

[31] https://www.tadawulgroup.sa/
[32] https://ereference.tadawul.com.sa/

After applying this criterion, the study establishes a sample of 686 firm-years across 21 sectors, covering the period from 2018 to 2023. Approximately 5.8% (42 firm-year observations) of the initial textual data extracted in Chapter 4 were excluded due to the criteria selection. Each firm in the current sample is represented by two versions of its annual report for a given year. Figure 6.2 displays the sample distribution by industry (Panel A) and year (Panel B) based on the SSE's sector classification, as reported in Table 6.1. Each firm is represented by two annual reports, one in Arabic and one in English, for a total of 1,372 observations

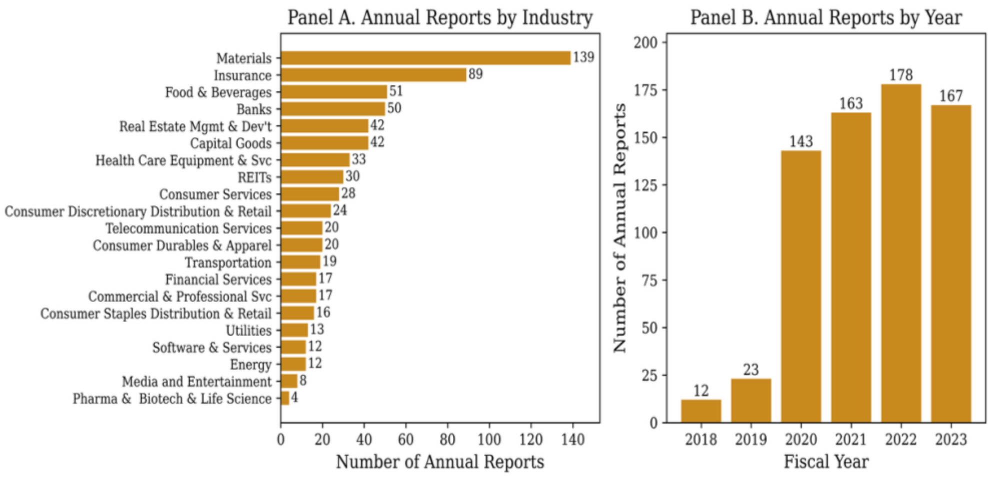

Figure 6-2 Distribution of the sample across the Saudi Stock Exchange industry sectors and years

6.4.5 Variable Construction

This section describes the construction of the dependent, independent, and control variables employed in the empirical analysis. The research aims to assess whether the ArFinSD's positive, negative, and uncertainty categories are associated with observable market reactions following the release of the annual report on the Saudi Stock Exchange. Additionally, the empirical analysis also considers the English versions of the annual reports, utilizing positive, negative, and uncertainty categories based on the LM dictionary.

6.4.6 Dependent Variable

The research uses the cumulative abnormal return (CAR) as the dependent variable across model specifications to observe the market reaction to the tone identified in the annual reports. CAR has been a standard measure of market reaction to an event and is widely employed in finance textual analysis research to explain and assess the role of sentiment on returns (Henry, 2008; Henry & Leone, 2016; Angelo et al., 2025; Davis et al., 2012; Azimi & Agrawal, 2021;

Do et al., 2025; Yekini et al., 2016) The objective of using CAR is to isolate the firm's expected stock return during the event window from the component that responds to the event, providing an empirical benchmark for evaluating whether the sentiment identified in the annual reports has explanatory power for market reaction.

The daily abnormal returns are computed using the market-adjusted model, in which the firm's returns are adjusted for the return on the Saudi Exchange index (TASI). The abnormal returns are then aggregated across the event window as follows:

$$CAR_{i,[t_1,t_2]} = \sum_{t=t_1}^{t_2} \left(R_{i,t} - R_{m,t}\right)$$

Where $R_{i,t}$ denotes the daily return on the firm and $R_{m,t}$ represents the market's corresponding return.

The analysis establishes short (CAR [−1, +1]), medium (CAR [−1, +5]), and long (CAR [−1, +10]) windows to examine market reactions, as illustrated in the preceding sections. The event window starts one day prior to the release of the annual report. For instance, CAR [−1, +1] denotes the cumulative abnormal return from the day prior to the annual report's release to the specified day after its publication.

6.4.7 Independent Variables

The research's key independent variables are the proportional sentiment words identified in the annual reports, in both Arabic and English, using the ArFinSD and LM dictionaries, respectively. These measurements are established in the preceding chapter and derived from the baseline sentiment classification analysis in Chapter 5, Section 5.3, which presented the sentiment classification results based on Arabic annual reports and their corresponding English versions. The proportional sentiment measure for each category (positive, negative, and uncertainty) is computed by dividing the number of sentiment words in that category by the total number of words in the annual report, after excluding stop words (See Chapter 4, Table 4.1 for details on stop words and word definition across Arabic and English reports). The proportional sentiment approach has been employed as a measure of sentiment to observe market reaction in prior research, including Azimi and Agrawal (2021), Bannier et al. (2019), Loughran and McDonald (2011), Price et al. (2012), Qin and Cui (2024), and Tetlock et al. (2008), The proportional sentiment categorical measurement allows the research to determine which sentiment category has market predictive power across the Arabic and English annual reports around the filing time.

6.4.8 Control Variables

The control variables employed in the study are based on the relevant literature and expected to be related to a firm's market response around the date of the annual report release. The research controls for the firm's size (Size), measured as the natural logarithm of market capitalization. Extensive empirical evidence has demonstrated that firm size captures systematic variation in stock returns (Banz, 1981; Fama & French, 1992). Dang et al. (2018) emphasized that firm size plays a critical role in empirical financial studies, as it influences cross-sectional results and must be carefully controlled. Firm size has been used as a control variable in numerous empirical studies analyzing the firm's tone in relation to short-term market reactions (Azimi & Agrawal, 2021; Boudt et al., 2018; Henry, 2008; Loughran & McDonald, 2011; Tetlock et al., 2008). Larger firms generally receive more analyst coverage, higher liquidity, and less information asymmetry, which may lead to different market reactions to narrative disclosures than those of smaller firms. Therefore, including firm size as a control variable helps isolate the incremental impact of sentiment on abnormal returns across different firm sizes.

Additionally, the book-to-market (B/M) ratio is included as a control variable, following prior research by Loughran and McDonald (2011), Tetlock et al. (2008), and Azimi and Agrawal (2021). The B/M ratio is calculated by dividing the book value by the market value at the end of the financial year. B/M is commonly regarded as a measure of company growth (Gaver & Gaver, 1993; Lang et al., 1996). B/M is a critical factor to control, as firms with a high ratio are either undervalued or facing financial constraints. Firms with low ratios are viewed as growth stocks, reflecting higher market expectations. Iwasaki et al. (2023) found that firms with greater growth opportunities, as measured by lower B/M, exhibit a stronger market reaction to tone.

The research includes share turnover (turnover) as a control variable, following Loughran and McDonald (2011) and Tetlock et al. (2008). Turnover is calculated as annual trading volume divided by the shares outstanding at the end of the fiscal year. Including turnover is intended to address liquidity, as it affects return dynamics. Firms with high turnover attract more participation, potentially affecting the magnitude of market reaction to sentiment in annual reports.

Lastly, the free-floating share of institutional ownership (Free-float Inst. Own) is included as a control variable. Loughran and McDonald (2011) include total institutional ownership to account for cross-firm differences in market microstructure and trading behavior. Due to the unavailability of a consistent measure of total institutional ownership for the SSE setting, the research employs a closely related measure, namely the percentage of free-floating shares held by institutional investors at the end of the fiscal year. The variable serves as an indicator of the institutional composition of the tradable shares and is used as a microstructure-related control consistent with the motivation noted in Loughran and McDonald (2011).[33] All continuous control variables are winsorized at the 1st and 99th percentiles. The size, B/M, and turnover are expressed in logarithmic (log) form, while the Free-float Inst. Own is included as a proportion.

6.4.9 Model Specification

After constructing the dependent, independent, and control variables, the research examines the market reaction to the proportional sentiment identified in the Arabic and English annual reports using the ArFinSD and LM dictionary, respectively, by estimating the following regression:

$$\begin{aligned} CAR_{it} = \beta_0 + \beta_1\, SENTIMENT_{it} + \beta_2\, SIZE_{it} + \beta_3\, BOOK\_TO\_MARKE_{it} + \beta_4\, TURNOVER_{it} \\ + \beta_5\, FREE\_FLOAT\_INST.OWN_{it} + \sum \beta(YEAR_t) + \sum \beta(INDUSTRY_j) + \varepsilon_{it} \end{aligned}$$

The research clusters standard errors by firm and includes year- and industry-fixed effects. Additionally, the model is estimated separately for each category (positive, negative, and uncertainty) and each language (Arabic and English). A variable definition table is provided in Appendix D.1.

6.5 Descriptive Statistics and Empirical Results

6.5.1 Descriptive Statistics

Table 6.2 presents summary statistics for the dependent variables, controls, and textual sentiment metrics used in the empirical analysis. Panel A presents the distribution of cumulative

[33] Re-estimating the regressions without the Free-float Inst. Own yields similar results.

abnormal returns across the study event windows ([−1, +1], [−1, +5], and [-1, +10]). The average CARs are close to zero, with values ranging from -0.009 in the medium window to -0.004 in both the short and long windows. The standard deviation increases with the event window length, reflecting greater price movement across longer event windows.

Panel B summarizes the control variables employed in the model. Firm size, book-to-market, and turnover are reported in natural logarithms. The sample demonstrates significant variation in firm size, ranging from 5.675 to 12.759. In addition, the Book-to-market variable is negative on average (mean -0.817; median -0.713), indicating that most firms in the sample have Book-to-market ratios below 1 (market values exceed book value). The turnover range in the sample reflects differences in liquidity across firms, with some experiencing high trading volumes. Institutional free-floating shares, reported as a proportion, show a mean of 0.071 (7%) across the sample, with values ranging from 0 to 0.437 (0- 43.7%). Together, the descriptive patterns of the control variables indicate substantial cross-sectional heterogeneity in the sample, reflecting the firms' characteristics within the Saudi Stock Exchange.

Table 6.2 Descriptive Statistics

Variables	Mean	SD	Min	50%	Max
Panel A: Dependent variables (CAR)					
CAR [−1, +1]	-0.004	0.034	-0.209	-0.005	0.144
CAR [−1, +5]	-0.009	0.050	-0.264	-0.013	0.258
CAR [−1, +10]	-0.004	0.065	-0.268	-0.010	0.359
Panel B: Control variables					
Log (size)	8.131	1.648	5.675	7.669	12.759
Log (B/M)	-0.817	0.674	-2.765	-0.713	0.470
Log (turnover)	0.359	1.427	-4.527	0.361	3.324
Free-float Inst. Own	0.071	0.086	0.000	0.046	0.437
Panel C: Positive sentiment					
Ar.Pos.	0.042	0.017	0.009	0.038	0.105
En.Pos.	0.022	0.010	0.002	0.020	0.058
Panel D: Negative sentiment					
Ar.Neg.	0.023	0.007	0.005	0.022	0.055
En.Neg.	0.016	0.007	0.003	0.015	0.052
Panel E: Uncertainty sentiment					
Ar.Unc.	0.018	0.006	0.001	0.017	0.040
En.Unc.	0.018	0.008	0.002	0.017	0.062

Continued

Table 6.2 (*Continued*)

The table presents descriptive statistics for the dependent variables, control variables, and sentiment metrics employed in the analysis. Panel A reports cumulative abnormal return (CAR) across three event windows measured from t-1 (relative to one day prior the annual report release date) through t+1, t+5, and t+10 days. Panel B presents firm-level control variables, including log (market capitalization), log (book-to-market), log (share turnover), and free-floating institutional ownership (as proportion). Panels C to E present sentiment metrics across two annual report versions: Arabic (Ar.) and English (En.). Sentiment classification employs a dictionary-based approach utilizing the Arabic Financial Sentiment Dictionary (ArFinSD) for Arabic reports and the Loughran and McDonald (2011) dictionary for English reports. All sentiment metrics are expressed as proportions representing the proportion of sentiment-bearing words relative to the total word count in each report. The sample comprises 686 firm-year observations for each variable. Variable definition list is provided in Appendix D.1.

Panels C to E report the share sentiment proportion calculated using the ArFinSD for the Arabic reports and the LM dictionary for the English counterparts' reports. The descriptive patterns across the study's sample demonstrate similarities to those reported in Chapter 5, Table 5.3. Positive sentiment, in panel C, remains the highest across all sentiment categories, with a mean of 0.042 (4.2%) in Arabic and 0.022 (2.2%) in English. Panel D reports the negative sentiment, which appears lower than the positive sentiment, averaging 0.023 (2.3%) in Arabic and 0.016 (1.6%) in English. The higher positivity in the annual reports across both languages, compared to the negative tone, is a consistent pattern identified throughout the research. Panel E reports the identified uncertainty words in both languages, indicating a high level of similarity (mean = 0.018 (1.8%)).

Table 6.3 reports the Pearson correlation coefficients among the CARs measures, firm-level controls, and the sentiment metrics employed in the analysis. All three CAR measures are significantly positively correlated with one another. Additionally, CARs show notably low correlations with the sentiment measure across languages. The Arabic and English sentiment categories exhibit a high correlation (e.g., 0.89 for negative, 0.93 for positive, and 0.88 for uncertainty), consistent with patterns observed in the preceding chapter. The Pearson correlation coefficients among variables indicate potential collinearity (e.g., between firm size and turnover). The study examined the effect of the linear relationship for the explanatory variables by calculating the variance inflation factor (VIF). Consequently, the observed values were fairly low (between 1.0 and 2.4), indicating no evidence of problematic multicollinearity.

Table 6.3 Pearson Correlation Coefficients

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) CAR [−1,+1]	1												
(2) CAR [−1,+5]	0.692***	1											
(3) CAR [−1,+10]	0.469***	0.758***	1										
(4) Size	0.083**	0.144***	0.072*	1									
(5) B/M	0.143***	0.159***	0.162***	-0.05	1								
(6) Turnover	-0.101***	-0.141***	-0.162***	-0.720***	-0.174***	1							
(7) Inst.Own	0.031	0.065*	0.025	0.310***	0.057	-0.336***	1						
(8) Ar.Pos.	0.026	0.029	0.04	0.510***	-0.072*	-0.360***	0.203***	1					
(9) Ar.Neg.	0.002	-0.045	-0.081**	-0.136***	0.109***	0.082**	-0.041	-0.278***	1				
(10) Ar.Unc.	0.026	0.022	0.028	-0.102***	0.171***	0.042	-0.052	-0.363***	0.576***	1			
(11) En.Pos.	0.03	0.019	0.026	0.449***	-0.071*	-0.299***	0.189***	0.935***	-0.319***	-0.400***	1		
(12) En.Neg.	0.007	-0.055	-0.106***	-0.185***	0.065*	0.143***	-0.080**	-0.301***	0.892***	0.524***	-0.331***	1	
(13) En.Unc.	0.039	0.032	0.035	-0.122***	0.141***	0.066*	-0.06	-0.334***	0.478***	0.889***	-0.350***	0.479***	1

Pearson correlation coefficients are reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.5.2 Empirical Results

The section presents regression estimates linking sentiment identified in Arabic annual reports and their English counterparts to cumulative abnormal returns around the release day. While the study examines negative, positive, and uncertainty tones, only the negative tone demonstrates predictive power across annual reports in both Arabic and English. The regression results indicate that only negative sentiment is associated with abnormal returns. For both languages, the coefficients for positive and uncertainty tones remain small and are not statistically significant in predicting observable market reactions across the study event windows. These estimates indicate that positive and uncertain sentiment words in annual reports do not provide a meaningful disclosure signal to explain abnormal returns. Given their lack of explanatory power, the research reports these results in Appendix D.2.

Therefore, Table 6.4 reports the effect of negative sentiment on cumulative abnormal returns across the immediate, medium, and long windows. A negative tone reveals a pattern of incremental relevance of information. Across all windows, the estimated coefficients for negative tone are negative, suggesting that a higher frequency of negative words is associated with lower abnormal returns; however, some event windows are not statistically significant. This pattern is consistent across both languages, measured by the ArFinSD and LM, although the timing and strength of the market's reaction differ across the two versions of the report. For Arabic annual reports, the estimated coefficients become gradually more negative across the event windows, reaching statistical significance at the 10% level on day 5 and at the 5% level on day 10. For English annual reports, the estimated coefficients become increasingly negative across the event windows; however, statistical significance is observed only on day 10, where the coefficient is significant at the 5% level.

Table 6.4 Cumulative Abnormal Returns

Explanatory variables	CAR [-1, +1]		CAR [-1, +5]		CAR [-1, +10]	
Panel A: Arabic Language						
Ar. Neg.	-0.129		-0.468*		-0.668**	
	(0.175)		(0.242)		(0.330)	
Log (Size)	0.003		0.004		-0.002	
	(0.002)		(0.003)		(0.004)	
Log (B/M)	0.007***		0.009**		0.011**	
	(0.003)		(0.004)		(0.005)	
Log (Turnover)	-0.001		-0.000		-0.006	
	(0.003)		(0.004)		(0.005)	
Free-float Inst. Own	-0.008		0.009		-0.014	
	(0.015)		(0.027)		(0.038)	
Panel B: English Language						
En.Neg.		-0.062		-0.428		-0.821**
		(0.187)		(0.263)		(0.342)
Log (Size)		0.003		0.004		-0.002
		(0.002)		(0.003)		(0.004)
Log (B/M)		0.007***		0.009**		0.011**
		(0.003)		(0.004)		(0.005)
Log (Turnover)		-0.001		0.000		-0.005
		(0.003)		(0.004)		(0.005)
Free-float Inst. Own		-0.007		0.009		-0.015
		(0.015)		(0.027)		(0.038)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	686	686	686	686	686	686
R-squared	0.089	0.089	0.099	0.098	0.112	0.113

The table presents results from event study regressions examining the association between negative sentiment and cumulative abnormal returns (CARs). Panel A reports results for Arabic-language sentiment extracted using the ArFinSD dictionary. Panel B reports results for English-language sentiment extracted using the Loughran and McDonald (2011) dictionary. Standard errors (reported in parentheses) are clustered at the firm level. Significance levels are denoted as *** (1%), ** (5%), and * (10%). Control variables include the log of market capitalization, the log of the book-to-market ratio, the log of share turnover, and free-float shares of institutional ownership. All regressions include year and industry fixed effects. The sample comprises 686 annual report filings from Saudi-listed firms over the period 2018-2023. Abnormal returns are calculated using the market-adjusted model.

Across both versions of the reports, a one-percentage-point increase in negative tone results in an estimated decrease in CAR of approximately 0.67% for the Arabic language and 0.82% for the English language. Correspondingly, a one-standard-deviation increase in negative tone is associated with a 0.47% decrease in CAR for Arabic and a 0.58% decrease for English over the 10-day window. Furthermore, the economic magnitude of the effect is modest relative to the overall variability of returns at the individual-firm level. According to Table 6.2, the standard deviation of the event window [-1, +10] is approximately 6.5%, which indicates that a one-standard-deviation increase in negative tone corresponds to roughly 0.07 to 0.09 standard deviations of ten-day CAR. These magnitudes suggest that negative tone has a statistically detectable price implication over the longer window, yet the effect remains moderate relative to the variations observed in abnormal returns.

Regarding the control variables, the log of the book-to-market ratio is positively and statistically significantly associated with cumulative abnormal returns across all event windows (CAR [-1, +1], CAR [-1, +5], and CAR [-1, +10]) in both language specifications. The coefficient on the book-to-market ratio increases from 0.007 in the short window [-1, +1] to 0.009 in the window [-1, +5], and 0.011 in the longer window [-1, +10]. The coefficients are statistically significant at the 1%, 5%, and 5% levels, respectively. In contrast, firm size, share turnover, and free-float share of institutional ownership are not statistically significant in either the Arabic or English specifications. Furthermore, the control-variable estimates are highly similar across the Arabic and English specifications, suggesting that the association between the included firm characteristics and cumulative abnormal returns is stable in both language settings.

To assess whether the association identified over the principal event windows persists over longer post-filing horizons, the research estimates CAR [-1, +15] and CAR [-1, +20] using the same model specification. Full results are reported in Appendix D.3, along with descriptive statistics for the CARs. For the Arabic annual reports, the negative sentiment coefficient remains statistically significant at the 5% level over the CAR [-1, +15] window, but its significance weakens to the 10% level over the CAR [-1, +20] window. For the English annual reports, the negative sentiment coefficient remains statistically significant at the 5% level over both extended windows. In contrast, positive and uncertainty sentiment remain statistically insignificant in both the Arabic annual reports and their English counterparts across the two extended periods. Combined with the results in Table 6.4, these findings show that the link between negative sentiment and abnormal returns continues beyond the CAR [-1, +10] window, although the statistical significance of negative sentiment in Arabic annual reports diminishes at the longest horizon.

More importantly, the results indicate that investors in the SSE do not treat all sentiment cues equally; instead, they respond selectively to pessimistic information. The results also indicate that no statistically significant association between negative tone in the annual reports and abnormal returns is observed over the short CAR [-1, +1] window. Instead, the association emerges over longer event windows, implying that participants incorporate narrative information contained in annual reports gradually. The delayed market reaction observed in this study is consistent with Loughran and McDonald (2011), who found that sentiment in annual reports does not translate into an observable next-day market reaction. However, the response delay observed in the current results is much longer. This longer adjustment period may reflect the inherent complexity and length of annual reports, which may require more time for market participants to process. Azimi and Agrawal (2021) argue that 10-K filings are complex and lengthy and may be overlooked even by sophisticated investors. The authors interpret the post-filing response to sentiment as evidence of market inattention to information in annual reports. Likewise, You and Zhang (2009) find that investors' responses to 10-K information are sluggish and that underreaction is more apparent for firms that release more complex filings. Given that retail investors in the SSE account for a substantial share of trading activity, constraints in processing corporate narratives may contribute to the gradual incorporation of managerial tone into prices.

The association between negative sentiment and abnormal returns around the filing is consistent with prior studies, such as Loughran and McDonald (2011), that have documented the explanatory power of negative tone in corporate disclosures. Similarly, the finding that a negative tone predicts market reactions agrees with Jegadeesh & Wu (2013) and Feldman et al. (2010). Although these studies, along with Yekini et al. (2016), find that positive tone is also related to market reactions, our results are similar to those of Loughran and McDonald (2011), which indicate that positive tone is not statistically associated with abnormal returns around the filing of annual reports. Additionally, the results for uncertainty tone differ from prior evidence reported by Loughran and McDonald (2011) and Bannier et al. (2019), which showed that uncertainty in tone is informative in their respective settings. Within the SSE, neither uncertainty nor positive sentiment is a meaningful predictor of observable market reaction.

The different associations across the sentiment categories in this research may also be considered in light of the investor composition of the SSE. As discussed in Section 6.2, the Saudi market is characterized by substantial retail participation in trading, and prior research shows that retail investors in the SSE exhibit attention-driven trading behavior (Alshammari & Goto, 2022). Evidence from the behavioral finance literature documents that retail investors tend to be net buyers of attention-grabbing stocks (Barber & Odean, 2008). Furthermore, Frank and Sanati (2018) also find that retail investors trade more strongly in response to positive news shocks than to negative news shocks. However, investors' tendency to pay greater attention to positive or favorable information does not necessarily imply a similar response to positive managerial tone in annual reports. Although positive tone may reflect favorable information, it can also serve other communication purposes. Huang et al. (2014) show that positive tone in corporate disclosures may reflect genuine financial performance or signal private information, but positive tone may also be used strategically to influence investor perceptions or obscure poor performance. Therefore, positive managerial tone does not necessarily carry only a favorable signal of the firm's value. In contrast, prior psychological evidence suggests that negative information receives greater attention and is processed more thoroughly than positive information (Baumeister et al., 2001; Rozin & Royzman, 2001). The greater cognitive weight given to processing negative information may help explain its significant association with abnormal returns in the SSE setting, while positive sentiment does not exhibit a significant association with returns.

In comparison, uncertainty tone does not inherently convey a positive or negative directional signal. Instead, it conveys an ambiguous or cautious managerial tone regarding the firm's trajectory. Prior research suggests that uncertainty language in managerial tone can complicate market participants' assessment of firm value and increase the information risk investors face (Ertugrul et al., 2017). In this respect, uncertainty in annual reports may make the disclosed information difficult for market participants to process. Dzieliński et al. (2017) find that market participants respond less strongly and more slowly when managerial communication is vague. Although uncertainty language is relevant to explaining different market phenomena, it may not translate into a directional response in abnormal returns following the release of annual reports. This may help explain the insignificant uncertainty coefficients in the SSE setting examined in this study.

From a bilingual reporting perspective, both annual reports show a high degree of similarity in market reaction. Neither version of the annual report creates a market reaction to a positive or uncertain tone. In both cases, only negative sentiment is statistically significant in predicting abnormal returns around the filing day. The findings suggest that neither disclosure language provides distinctive sentiment cues that lead to different return dynamics. Instead, investors, whether relying on the Arabic version or its English counterpart, are exposed to broadly similar information. The current evidence regarding the bilingual tone in SSE differs from that reported by Do et al. (2025), who found that only the local language is informative in explaining subsequent market reactions to annual reports. The slightly earlier emergence of statistical significance for the negative tone coefficient in the Arabic version on day 5 may reflect the SSE market's characteristics, particularly the predominance of local investors. Domestic investors may incorporate the sentiment conveyed in the Arabic version of the annual report into prices more quickly than the sentiment conveyed in the English version.

In sum, the SSE appears to incorporate negative tone from both Arabic and English annual reports into prices, but it does so gradually rather than immediately. The association with negative tone is not evident over the short CAR [-1, +1] window in either language. Additionally, the results reveal that positive and uncertainty do not exhibit a measurable market return response. Furthermore, the results are broadly similar across the Arabic annual reports and their English counterparts, although the negative sentiment association becomes statistically significant earlier for the Arabic reports. Thus, the empirical evidence supports H1a and H1b over the long window. Furthermore, the supplementary analysis shows that the association between negative sentiment and abnormal returns persists over CAR [-1, +15] and CAR [-1, +20], but the statistical significance of the Arabic coefficient diminishes at the longest horizon. In contrast, no support is found for H2a-H2b and H3a-H3b across either the principal or the extended event windows in either language.

6.6 Study Limitation

Although the study provides insight into the tone of bilingual reporting in the SSE when using the ArFinSD and the LM dictionary as measurement tools, it does have certain limitations. First, the sentiment matrices are driven using the dictionary-based approach and NLP implementations for each language, as outlined in the previous chapters. Although both languages relied on domain-specific dictionaries to measure sentiment in annual reports, the classification method depends on predefined sentiment categories. Therefore, it may not fully capture syntactic and semantic relationships in the text. Second, the study aims to assess the explanatory power of the sentiment identified in the annual reports. The market reacts negatively to a negative tone, as shown by the sentiment coefficient across the event windows and the statistical significance in the ten-day window at the 5% level. The findings, however, also indicate that the overall explanatory power of the study's regression analysis is modest. This is reflected by the model's adjusted R-squared (around 7% for both languages in the ten-day window), which indicates that the model explains only a limited fraction of the variation in CARs. This issue has been raised by Loughran and McDonald (2011), who reported an adjusted R-squared of around 2.6%, suggesting that textual analysis alone does not provide a definitive explanation for returns. Third, our findings reflect the unique regulatory environment in Saudi Arabia and its stock exchange. The results may not be generalized to other emerging markets with distinct discourses and regulatory structures across Arabic-speaking countries. Lastly, the study period includes the COVID-19 shock, during which the SSE experienced uncertainty and shifts in trading behavior. The relationship between negative sentiment and CAR may partly capture crisis-specific language and trading behavior, limiting the generalizability of the results to more stable market conditions.

6.7 Concluding Remarks

This chapter applied the newly developed ArFinSD, together with the LM dictionary, to empirically examine sentiment in annual reports filed by Saudi-listed firms from 2018 to 2023. Using an 686 firm-year sample, we examined the market reaction to narrative tone (positive, negative, and uncertainty) in a bilingual setting, employing an event-study methodology. Most studies rely on a single language to evaluate subsequent market reaction to tone in annual reports. In this study, we measure sentiment in annual reports in Arabic and English. The study contributes to the literature on the role of tone in financial disclosures in a bilingual reporting environment.

The study's results suggest that neither version of the annual report provides distinctive informative signals, and participants respond to both versions in a broadly similar manner. Our empirical results differ from those of Do et al. (2025), who show that tone is conveyed differently in the local language (Chinese) compared to the English version of the annual report. Within the context of the SSE, the study's results show that the market responds similarly to both versions of the annual reports.

The research reveals that a negative tone has explanatory power related to market reactions, whereas positivity and uncertainty do not. Specifically, an increase in negative tone is associated with a statistically significant decrease in CARs following annual report filings. This finding aligns with prior research documenting the importance of negative tone as a critical cue in creating subsequent market reaction. The study shows that participants in the SSE view pessimistic language disclosures as an informative signal.

Additionally, the study finds that the delay in market reaction to negative sentiment indicates that the market gradually incorporates annual report content into prices after the filing release date. We observe no significant price adjustments in the short [−1, +1] window. Instead, the negative sentiment effect emerges and becomes statistically significant for Arabic annual reports in the [−1, +5] window and for English annual reports in the [−1, +10] window. Additionally, the extended-window analysis of [−1, +15] and [−1, +20] windows further shows that the effect of negative tone remains reflected in returns after the release of the annual reports, as evidenced by the statistically significant Arabic and English coefficients. The delay in market reaction could be attributable to the complexity and the length of the annual report, as highlighted in similar studies (Azimi and Agrawal, 2021; Loughran and McDonald, 2011).

Despite its contribution, the study has several limitations that may influence its findings. The dictionary-based textual sentiment classification approach may not capture the full semantic relationships between words, thereby affecting accuracy. Also, only a slight variation in returns is explained by the explanatory negative sentiment variable, which may limit the explanatory power of the textual sentiment. Other limitations stem from the market and data sample under study, such as the strict bilingual reporting environments and the effects of COVID-19 on trading behavior.

Chapter 7. Conclusion

7.1 Introduction

This chapter brings together the thesis contributions on financial textual analysis and considers their implications for the ASA and finance literature. The research advances the ASA and finance literature, where the necessary tools are scarce and financial textual analysis is limited. The study was motivated by the lack of appropriate Arabic finance-oriented sentiment tools for capturing sentiment in financial texts and by the need to develop a financial sentiment dictionary. In addition, the Arabic-English language pair poses challenges for MT tasks and may lead to sentiment loss in financial narratives. To that end, the research sought to advance our understanding of the effect of MT on textual sentiment. Also, in corporate communication, Saudi firms disclose information in Arabic and English. In this bilingual reporting setting, the study further offers new insights into how textual sentiment conveyed across the two language versions is associated with market reactions. This chapter concludes the thesis by presenting key findings, contributions, practical applications, practical implications, limitations, and future directions.

7.2 Key Findings

The research provides several key insights that advance our understanding of the linguistic and empirical role of sentiment in Arabic corporate financial reporting narratives and their implications for market responses. First, Arabic financial narratives require specialized tools to capture sentiment accurately. The research demonstrates that, when using a finance-oriented dictionary, such as the ArFinSD, the tone of corporate reporting is accurately captured. The findings align with those from similar studies in other languages (Henry & Leone, 2016; Loughran & McDonald, 2011, 2015; Bannier et al., 2019), emphasizing that the finance domain requires a specialized dictionary to capture the sentiment in business communication. The study confirms that general Arabic dictionaries are not appropriate for capturing sentiment in financial texts, either because they misclassify words or because they are too broad to reflect managerial tone effectively. In Chapter 5, the study found that the general dictionary ArSenL frequently misclassifies sentiment across all categories, significantly affecting the analysis results. Furthermore, the research highlighted that dictionaries such as ArSenL include stop words and function words that lack sentiment value in financial contexts. Including these words dilutes the essential managerial tone.

Second, the research reveals that negation plays a critical role in expressing sentiment in financial narratives. In the cross-language comparison settings outlined in Chapter 5, Section

5.4, the findings indicate that negation is extensively used in Arabic financial narratives to convey positive or negative sentiment. These findings have important implications for sentiment classification of financial narratives. The research findings suggest that negation must be applied to both sentiment scales to accurately reflect the intended sentiment. In English narratives, it has been argued that the negation of negative words is rare in corporate disclosures (Loughran & McDonald, 2011). Nevertheless, the research findings suggest that the use of negation in English narratives is advantageous for accurately reflecting both negative and positive sentiments.

Third, the research finds that, within the context of Saudi bilingual annual reports, MT largely preserves the overall sentiment pattern in Arabic-English financial narratives to a large extent. This is critical, as a large body of CLSA literature has used machine-translated documents for sentiment analysis. However, sentiment preservation under MT remains underexplored in Arabic financial narratives. The research, using a bidirectional experiment, reveals that MT yields sentiment indicators comparable to those in the original corporate disclosures across the Arabic and English annual reports. The findings indicate that when translating corporate disclosures written in the MSA style, sentiment is broadly preserved at the document level. Moreover, the experiment shows that translation in the English-to-Arabic direction is more stable for sentiment preservation.

Lastly, the research provides empirical evidence that textual sentiment in annual reports is reflected in returns in the SSE. Using a bilingual tone framework, the analysis shows that only the negative tone in both Arabic and English reports is associated with CARs following the annual report release. In addition, the empirical analysis reveals that the SSE does not immediately respond to negative sentiment conveyed in annual reports, suggesting investors may require more time to process large volumes of information. The analysis also sheds light on the bilingual reporting environment in the SSE. The finding shows that the SSE responds similarly to the negative tone conveyed in the Arabic and English annual reports, though the response is delayed. The results reveal that Arabic annual reports and their English counterparts reflect broadly comparable textual sentiment signals despite the linguistic differences.

7.3 Research Contributions

The thesis introduces the Arabic Financial Sentiment Dictionary (ArFinSD), the first comprehensive Arabic-language dictionary designed for Arabic financial applications. The dictionary addresses a fundamental limitation in Arabic financial literature: the lack of a robust, domain-specific resource that reliably captures sentiment in financial narratives. Prior research demonstrates the importance of domain-specific dictionaries in financial textual analysis, showing that finance-oriented sentiment dictionaries provide more accurate sentiment classifications than general sentiment dictionaries (Loughran & McDonald, 2011; Henry & Leone, 2016). Researchers have since extended this approach to other languages, such as German (Bannier et al., 2019) and Spanish and Portuguese (González et al., 2021). The ArFinSD extends this domain-specific approach to Arabic financial narratives. It is constructed by mapping the Loughran and McDonald (2011) financial dictionary, a predominant English resource in the finance and accounting literature. Additionally, its construction required accounting for several linguistic aspects inherent to Arabic, including morphological and inflectional richness, ambiguity in surface forms, and the financial interpretation of its diverse lexical variants. To address these challenges, the thesis implements a lemmatization-based dictionary construction approach, providing a robust finance-oriented tool for the Arabic language.

The ArFinSD is constructed through a multi-stage process that includes: (1) translation alignment between the LM dictionary entries and Arabic translation candidates, (2) incorporation of n-gram expressions as multidimensional entries, (3) manual verification of word usage and sentiment category, and (4) establishment of a lemma-based dictionary. The lemma-based approach aligns with established general Arabic sentiment resources, such as ArSenL and SLSA, which both use lemmas as their lexical representation to account for Arabic morphological variation (Badaro et al., 2014; Eskander & Rambow, 2015). The ArFinSD is organized into three sentiment categories: Positive, Negative, and Uncertainty. The dictionary is further organized by dimensionality, providing a more comprehensive linguistic tool for accurately capturing tone in business communication. To ensure maximum flexibility for future research, the thesis provides two complementary versions of the dictionary: a lemma-form version, aligned with the morphological pipeline employed in this research, and an original-form version used in the preliminary phase after translation. For easier adoption and seamless integration, Appendix A presents the dictionary in three structured formats:

- An original-form dictionary with corresponding English entries from the LM dictionary.
- A lemma-form dictionary with corresponding English entries from the LM dictionary.
- A dimensionally structured lemma-form dictionary organized into unique unigram, bigram, and trigram entries.

By providing these versions of the dictionary, the research contributes to broader methodological applications by allowing the dictionary to accommodate studies that may adopt alternative word representations (e.g., stemming or surface forms) or alternative morphological procedures. By providing both structural versions, the thesis allows researchers to select the most suitable dictionary format that best aligns with their methodological frameworks and linguistic constraints.

Each sentiment category is regarded as an essential indicator of tone in the finance literature and has been used to explain or uncover market phenomena. However, uncertainty tone is highly domain-dependent. The ArFinSD's uncertainty category adds a distinct dimension to researchers' assessments of uncertainty tone in financial narratives. While positive and negative sentiment are typically reflected at opposite ends of the scale, uncertainty captures a distinct dimension of financial narratives that has received considerable attention in English textual analysis. In Arabic sentiment analysis, however, uncertainty tone is largely overlooked, and general Arabic sentiment dictionaries, such as ArSenL, lack a corresponding uncertainty category. The additional uncertainty words, such as *may* (رُبَّما), *unclear* (مُبْهَم; غامِّض;غَيْر واضح), and *unknown* (مَجْهُول; غَيْر مَعْرُوف), provide a valuable dimension for research in Arabic narratives, as prior work in English has demonstrated that uncertainty and ambiguous language are associated with several financial outcomes, such as market reactions, borrowing costs, and information asymmetry (Loughran & McDonald, 2011; Ertugrul et al., 2017; Black et al., 2025). By explicitly including a finance-oriented uncertainty category, the ArFinSD extends this line of textual analysis to Arabic financial narratives.

In addition to constructing the ArFinSD, the thesis makes a further contribution by providing a transparent, replicable workflow for applying dictionary-based sentiment analysis to Arabic financial narratives. A key advantage of the dictionary-based approach is its simplicity and replicability. However, because Arabic exhibits substantial morphological complexity and NLP resources are scarce and vary in performance, the steps involved in applying the dictionary-based approach are neither straightforward nor well documented. Chapter 4 provides a practical, step-by-step framework for future research. This is particularly important when selecting and applying normalization techniques. The chapter outlines various libraries that offer normalization techniques, including lemmatization and stemming. It conducts an evaluation of these libraries for applying these techniques to the ArFinSD or employing the dictionary-based approach to capture tone in financial narratives. The research presents different analyses using different word representations (e.g., lemmatization and stemming). The lemmatization technique using CAMeL's MLE and BERT-based models yields highly similar sentiment classification results across the two models and provides finance-domain-appropriate options for researchers wishing to apply dictionary-based sentiment analysis to Arabic financial narratives.

The research also contributes to the finance literature by providing empirical evidence of the SSE's reactions to textual sentiment in a bilingual reporting environment. Much of the established literature examines the role of tone in corporate disclosures in monolingual English settings (Feldman et al., 2010; Loughran & McDonald, 2011). This study adds a new dimension by examining tone across Arabic and English annual reports. The SSE has undergone substantial regulatory reforms in recent years and is considered the largest capital market in the MENA region. Additionally, the Saudi government has sought to relax regulations and liberalize the capital market to attract foreign investments. The analysis shows that the negative tone in both Arabic and English annual reports issued by Saudi-traded firms is negatively associated with CARs. The results, therefore, extend prior evidence on the association between pessimistic disclosure language and market reactions from English-language and developed markets to a low-resource language and an emerging market. To that end, by demonstrating the role of textual sentiment in market reactions, the study establishes a benchmark for future work on Arabic financial narratives and bilingual corporate reporting.

7.4 Practical Applications

The ArFinSD offers several practical applications for researchers, analysts, and policymakers working with financial narratives expressed in MSA across the Arabic-speaking countries. As a finance-oriented dictionary, it provides a specialized linguistic tool for extracting sentiment from business narratives that rely on MSA as a medium of communication. Because corporate disclosures and formal business communication documents across Arabic-speaking countries are issued in standardized MSA rather than dialectal forms, the dictionary provides an easy and accessible tool for sentiment analysis in a variety of applications.

The ArFinSD can be used for a range of corporate disclosures beyond the annual report and its components (e.g., CEO letters, MD&A, chairman letters). These include corporate disclosures such as IPO prospectuses, earnings announcements, and environmental, social, and governance disclosures. Additionally, the ArFinSD is suitable for analyzing narratives in credit rating reports and in government agencies' economic reports. For example, the Central Bank and the Ministry of Finance publish periodic economic reports. These documents may contain valuable information that could affect financial markets. The dictionary is also appropriate for a broad range of market research materials, analyst reports, and financial news, all of which constitute critical information sources in financial markets.

The ArFinSD can provide practical value to regulatory bodies, investment portfolio managers, and communication officers. Regulatory bodies can use the dictionary in automated systems to assess narrative consistency and reporting quality. This is important to ensure transparency and regulatory compliance in corporate reporting practices. In addition, the ArFinSD could be a valuable resource for identifying early warning signals of financial risk and economic constraints. Managerial tone provides critical incremental information beyond what quantitative information reflects. Soft information may convey a forward-looking trajectory rather than backward-looking or historical performance. Identifying such forward-looking signals may help portfolio managers adjust their trading strategies or investment allocation.

Furthermore, the ArFinSD can be integrated into hybrid sentiment classification models, thereby enabling broader practical applications in Arabic NLP projects. Shi and Agrawal (2025) emphasize the importance of Arabic sentiment dictionaries in addressing critical shortcomings in Arabic NLP. Sentiment dictionaries are essential for low-resource languages such as Arabic and for handling domain-specific narratives that are underrepresented in training data. To that end, the ArFinSD can be used as a feature-extraction tool to filter for relevant sentiment information in business communication narratives. The dictionary can help identify the most relevant sentiment-bearing terms that align with the model's goal (e.g., terms linked to negative-bearing words or to an uncertainty tone) across different classification levels (e.g., sentence or document). The dictionary can also help filter out irrelevant information that lacks sentiment connotation in business communication. This is critical in large projects to minimize noise and identify only sentiment-bearing and finance-relevant data.

Additionally, since the ArFinSD is designed for Arabic financial applications, it can be used during the training phase to weakly label extensive Arabic financial datasets. For example, Sheetal and Aithal (2025) used the LM dictionary for data labeling, leveraging its predefined finance-oriented lists. By relying on the LM dictionary as a labeling reference, the model's prediction accuracy increased substantially. This approach can overcome the manual labeling process, which is believed to be costly and labor-intensive.

Furthermore, Shi and Agrawal (2025) document additional sentiment-dictionary applications, including feature augmentation and interpretability, for which the ArFinSD may prove beneficial. For example, the ArFinSD could be incorporated into hybrid deep learning architectures, enabling the model to integrate it during training. This may allow models to improve sentiment classification accuracy, as ArFinSD provides an additional layer of information that guides the model's identification of financial sentiment. Similarly, the ArFinSD can provide a clear framework for how certain words contribute to sentiment output when combined with a sentiment dictionary and advanced sentiment classification models. This can minimize the black-box problem in which models fail to explain how an input becomes an output.

7.5 Practical Implications

The research findings offer practical implications for investors, researchers, and policymakers. First, the evidence of an association between negative sentiment in annual reports and returns following their release suggests that investors in the SSE should pay close attention to pessimistic language conveyed in narrative disclosures. Positive and uncertainty language, in contrast, does not provide incremental cues that translate into observable market reactions in the research's empirical setting. For local and foreign investors, the findings indicate that negative managerial tone may provide useful sentiment signals regarding the firm's performance beyond the quantitative financial information.

Second, the bilingual tone analysis shows that negative tone in the Arabic and English versions is reflected in subsequent market reactions, and that the tone in the English version tracks that of the Arabic version. This finding suggests that international investors who rely primarily on the English version of the annual report do not miss distinctive sentiment cues reflected in the Arabic version. The finding is also valuable to policymakers and market regulators in the SSE. International investors require high compliance with corporate governance standards and transparency in corporate reporting. Given the growing participation of foreign investors, as discussed in Chapter 6, regulators should continue to monitor the bilingual reporting environment and encourage high-quality, accurate reporting practices.

Third, the findings on MT in Arabic-English financial texts offer valuable practical implications for researchers. Although the experiment was conducted under specific conditions and within a defined evaluation framework, the findings may encourage researchers to employ MT to address the scarcity of NLP resources in low-resource languages. In particular, sentiment analysis of financial texts has consistently been shown to require domain-specific resources. The findings show that even when employing MT between Arabic and English, a challenging language pair for MT, the sentiment is largely preserved at the document level. The findings therefore suggest that researchers may mitigate resource scarcity in their target languages by automatically translating financial texts into English, which is rich in finance-oriented resources.

7.6 Research Limitations

The research acknowledges and addresses several limitations in its relevant chapters; however, it is worth noting several constraints that may influence the research findings or its contributions. First, the ArFinSD is constructed using Modern Standard Arabic (MSA), the official standardized variety used in formal communication. Arabic sentiment analysis distinguishes between MSA and dialectal Arabic, which is commonly used in informal communication and varies across Arabic-speaking regions (Ghallab et al., 2020). In addition, MSA is a standardized form commonly used in formal writing, whereas dialectal Arabic shows greater linguistic variation and has fewer available NLP resources for its processing (Abdul-Mageed et al., 2014). The ArFinSD, therefore, is not suitable for capturing sentiment in dialectal or informal language across communication channels, such as social media, blogs, interviews, or conference transcripts. This may limit its usability to formal business writing.

Second, the Arabic textual analysis is based on the lemmatized word entries. Although lemmatization can group morphologically distinct word forms into a lookup form, known as a lemma, retaining inflected word forms in dictionary-based sentiment classification has been shown to improve classifier accuracy compared with further normalized forms (Loughran & McDonald, 2011; Bannier et al., 2019). This is because in lemmatization-based sentiment analysis, the identification of the correct lemma within the text depends on the model's capabilities to disambiguate the text and correctly identify the lemma. This limitation stems from Arabic's inherent morphological complexity, where nouns and verbs can be inflected to a large number of forms across different morphological features (Shilon et al., 2010). The research also considered stemming as an alternative normalization technique; however, the results reported in Appendix B.3 indicated that stemming aggressively reduces word forms to their common roots, substantially reducing sentiment classification accuracy. To mitigate this limitation, the research employs the CAMeL Tools MLE morphological disambiguator, for which Obeid et al. (2020) report achieving 95.7% accuracy in lemma prediction for MSA.

Third, the research also acknowledges limitations in cross-language sentiment analysis. Arabic and English belong to different language families, and there is substantial disparity in their morphological and grammatical systems. Such differences are manifested in the research's NLP implementation for each language. For example, in Arabic, multidimensional word entries are adapted to increase the likelihood of identifying negative phrases that correspond to English negative words, with negation cues embedded (e.g., disqualify, insufficiently, and misinterpret). Additionally, negation is a critical linguistic aspect in sentiment analysis, as it can alter sentiment polarity (Touahri & Mazroui, 2021), while Arabic negation takes several forms and can occur through different constructions (Kaddoura et al., 2021). The study sought to mitigate such differences by incorporating multiple negation forms in Arabic sentiment classification. However, additional negation forms and constructions may occur in financial texts and affect the accuracy of sentiment classification, requiring close examination.

Fourth, the research evaluates the impact of MT on financial sentiment using specifications that may limit the generalizability of its findings across different frameworks and languages. Prior research indicates that MT can preserve sentiment to a considerable extent in Arabic-English translation, although translation may also introduce differences in sentiment classification between Arabic and English texts (Mohammad et al., 2016). The study evaluates sentiment preservation using a dictionary-based approach, applying the LM dictionary and ArFinSD to annual reports of Saudi-traded firms. Although both versions are produced by the same firm and mandated by the same legislative body, the results cannot isolate the translation effect from the report's communication style. Furthermore, the research relies on document-level sentiment indices and a statistical agreement framework to assess sentiment preservation. Arabic-English MT performance may also vary by translation direction (Ameur et al., 2020). Thus, while the results suggest a high level of agreement between original and auto-translated annual reports, they should not be readily generalized without caution to other languages, markets, translation directions, or MT systems.

Lastly, the research empirically examines the bilingual tone environment on the SSE. While Chapter 6 addresses detailed limitations associated with the empirical analysis, some constraints are worth considering when interpreting and generalizing the findings. For example, the study's sample includes the COVID-19 pandemic, which represents an exceptional macroeconomic shock that may have influenced managerial tone and market participants' behavior. Consistent with this concern, Sayed and Eledum (2023) document a short-run reaction in the SSE following the announcement of the first confirmed COVID-19 case in Saudi Arabia. Although year and industry fixed effects are included to mitigate common time and sector influences on tone and returns, it remains difficult to separate the COVID-19 impact from managerial tone and returns under normal market conditions. Additionally, the study's findings on the similarity between the two versions of the annual reports in their association with market reactions should be interpreted with caution when considering other emerging markets. Since 2007, Saudi Arabia has implemented a series of capital market infrastructure reforms that have strengthened regulatory oversight, with evidence of improvements in aspects of financial reporting quality (Alsuhaibani et al., 2023). Additionally, with the introduction of Vision 2030, the Saudi capital market has undergone further reforms to support the government's objective of making the Kingdom a global financial hub (Vision 2030, 2025b). In this environment, managers may be more cautious when crafting the annual report in both versions to ensure they are close counterparts, and the degree of bilingual similarity observed in the current research should not necessarily be expected in other emerging markets with different regulatory environments.

7.7 Future Research Directions

In light of the research findings and contributions, several avenues are worthy of future exploration. First, the ArFinSD provides an important Arabic NLP resource for financial applications and offers a foundation for further lexical development. Future research could expand its coverage to address the lexical richness of the Arabic language. A widely used technique for developing or extending sentiment dictionaries is the seed approach, whereby the dictionary begins with an initial seed of words and is subsequently used to identify synonyms and related terms. Pöferlein (2021, 2023), for example, applied this approach to extend the finance-oriented sentiment dictionary established by Bannier et al. (2019) by incorporating additional sentiment words relevant to German business communication. Applying a similar procedure to the ArFinSD could identify additional sentiment terms relevant to Arabic financial narratives and enhance the dictionary's coverage of language-specific financial sentiment words.

Second, incorporating the negation effect into a dictionary-based approach can enhance sentiment classification by accounting for polarity reversal. Prior financial studies have employed different negation-scope windows, ranging from one word (Huang et al., 2014) to two words (Borochin et al., 2018) and three words (Loughran & McDonald, 2011; Correa et al., 2021), yet their comparative performance in financial narratives remains unexplored. Future research may evaluate additional Arabic negation forms and alternative scope windows to determine which window specifications can accurately capture the polarity reversal in Arabic financial narratives. This is particularly important because negation has a greater impact on sentiment classification in Arabic financial narratives than in their English counterparts, as demonstrated in Chapter 5, Section 5.4. Furthermore, Arabic negation is linguistically complex and expressed through diverse forms (Touahri & Mazroui, 2021; Kaddoura et al., 2021). Therefore, future studies could examine whether the relevance and scope of negation forms differ between general Arabic text and financial narratives, thereby supporting the development of domain-specific negation specifications for Arabic financial sentiment analysis.

Third, researchers may consider capturing tone within particular narrative sections of the annual report, such as the chairman's message, the risk assessment section, and the MD&A section, rather than measuring tone at the aggregate document level. Prior research indicates that tone within annual report sections may convey distinct information. For example, changes in MD&A tone have been associated with an immediate market reaction, while pessimistic MD&A language has been linked to subsequent operating performance (Feldman et al., 2010; Davis & Tama-Sweet, 2012). Similarly, managerial letters, such as the chairman's letter or president's letter, may provide managerial explanations and interpretations beyond the information contained in the financial statements (Abrahamson & Amir, 1996). Section-level analysis can be particularly valuable for Arabic financial narratives because high-performance text extraction and parsing tools remain scarce and unreliable (Faizullah et al., 2023; Kasem et al., 2025). Concise narrative-style sections can provide insights into the firm's current performance, corporate trajectory, and future performance. In the SSE, where retail and other non-institutional investors account for a substantial proportion of market activity (CMA, 2020; Alshammari & Goto, 2022), focused narrative-style sections can provide more focused insight into managerial tone and require less processing effort than complete annual reports, whose textual content is costly and time-consuming to process (Li, 2006). Future research could therefore examine whether the tone captured in these sections is more strongly associated with market reactions than the tone measured at the aggregate annual-report level.

Fourth, the research examines the market's reaction to tone in annual reports primarily through cumulative abnormal returns. However, textual sentiment may also be reflected in other dimensions of market activity, particularly trading volume and return volatility. Prior financial textual analysis studies show that textual information in corporate disclosures is associated with trading volume and return volatility around filing dates (Loughran & McDonald, 2011; Kravet & Muslu, 2013). Recent evidence indicates that managerial tone can be associated with abnormal trading volume and different trading responses across investor groups, such as large and small investors (Pouryousof et al., 2022), while uncertainty tone may affect information asymmetry and investor trading behavior (Black et al., 2025). These alternative measures may be particularly relevant to the SSE, where retail and other non-institutional investors account for a substantial proportion of market activity (CMA, 2020; Alshammari & Goto, 2022). Therefore, future research could examine whether negative, positive, and uncertainty tones in annual reports are reflected in trading volume and volatility after filings, as these alternative measures may reveal market responses to positive and uncertainty tones that were not captured through cumulative abnormal returns.

Fifth, the development of the ArFinSD creates new opportunities to examine sentiment divergence across various corporate communication channels. The current research primarily examines sentiment consistency between annual reports in Arabic and their corresponding English versions at the document level. Nonetheless, managerial tone may vary across disclosure outlets and language versions, depending on their purpose, format, and intended audience. For example, Davis and Tama-Sweet (2012) show that managers systematically use different language styles across earnings press releases and corresponding MD&A disclosures. In addition, recent studies suggest that divergence in tone at the managerial level and across textual sources may itself contain distinct information (Angelo et al., 2025; Garcia, 2025). Future research could examine annual reports, managerial letters, earnings announcements, and other firm disclosures to determine whether managerial tone remains consistent across these communication channels.

The bilingual reporting environment in the SSE also adds a further dimension to examining sentiment divergence across language versions. Although the research findings indicate broad sentiment consistency across Arabic and English counterparts, future research could examine whether the degree of sentiment divergence varies across different corporate disclosure types. This is particularly important when corporate disclosures target different investor audiences. Bao and Wei (2024), for example, find that Chinese firms issuing ESG reports in both Chinese and English attract greater foreign investor participation, suggesting that English-language disclosures may play an important role in reaching international investors. In the SSE, future research may investigate whether cross-language sentiment divergence is more pronounced in particular disclosure outlets and whether such divergence has informational implications as foreign participation in the Saudi market continues to increase.

Lastly, researchers may move beyond market reactions to returns and examine textual sentiment in relation to subsequent firm performance and fundamentals. The present research finds that the negative tone is associated with subsequent market reactions in the SSE, while the positive and uncertainty tones show no significant association with cumulative abnormal returns. However, the informational value of positive and uncertainty tones may extend beyond the immediate market reaction and be reflected in subsequent firm fundamentals over a longer horizon. Annual report narratives contain managerial assessments of current performance, operating conditions, risks, and future prospects that may later be reflected in firm fundamentals. Azimi and Agrawal (2021) find that positive and negative tone in 10-K filings predict future profitability and operating cash flows, as well as subsequent corporate policies such as cash holdings and leverage. Future research could use the ArFinSD to examine whether positive, negative, and uncertainty tones in Arabic annual reports and other corporate disclosures predict subsequent firm fundamentals, including profitability, operating cash flow, and other measures of financial performance. This direction may provide further insight into whether Arabic textual sentiment contains forward-looking information beyond what the immediate market reaction captures.

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Chapter 3 - Appendix A

Appendix A - The Arabic Financial Sentiment Dictionary (ArFinSD)

The appendix details and reports the Arabic Financial Sentiment Dictionary (ArFinSD) in three forms: (1) translating the Loughran and McDonald (LM) dictionary into original Arabic forms; (2) creating lemmatized Arabic equivalents aligned with the corresponding English LM sentiment words; and (3) finalizing the Arabic financial sentiment dictionary with unique entries organized by n-gram dimensionality (unigram, bigram, trigram). The following tables are organized by sentiment category and process stage. The negative list reported omits 365 English inflected forms ending in -s (e.g., plural or third-person singular verbs). These forms do not reflect new lemma Arabic translation candidates (e.g., violator and violators).

Table A1. (a-1) Positive English to Original Arabic Translation *(N =980)*

No.	English Word	Arabic Translation
1	able	قادر
2	abundance	وفرة، غزارة
3	abundant	وفرة، غزير، وفير، وافر، زاخر
4	acclaimed	مرموق، مشهود له
5	accomplish	ينجز، يحقق، إنجاز، يحرز
6	accomplished	أَحْرِزَ، أنجز، إنجاز، حقق
7	accomplishes	ينجز، يحقق، يحرز
8	accomplishing	ينجز، يحقق، يحرز، إنجاز
9	accomplishment	إنجاز، منجز
10	achieve	ينجز، يحقق، يحرز
11	achieved	أنجز، حقق، محرزة، محققة، أحرز
12	achievement	إنجاز، منجز
13	achieves	ينجز، يحقق، يحرز
14	achieving	ينجز، يحرز، تحقيق، إنجاز، يحقق
15	adequately	بشكل مُلائِم، بصورة مُلائِمة، بطريقة مُلائِمة، نحو مُلائِم، نحو كافي، بشكل كافي، بطريقة كافية، بصورة كافية
16	advances	التقدم، يتقدم
17	advancement	تطور، التقدم
18	advancing	تطوير، التقدم، يتقدم
19	advantage	مزايا، تفوق، ميزة، أفضلية، الميزة
20	advantaged	مميز، ميزة
21	advantageous	مواتٍ، نافع، مفيد
22	advantageously	بشكل مفيد، بصورة مفيدة، بطريقة مفيدة، نحو مفيد، على شكل مفيد، على نحو مفيد، على طريقة مفيدة، بشكل نافع، بصورة نافعة، بنحو نافع، بطريقة نافعة
23	alliance	تحالف، ائتلاف، اتحاد، الحلف
24	assure	طمأنة، يضمن، يؤكد، يؤمِّن، يطمئن
25	assured	ضَمِن، أكد، طمأن، مؤكد، مطمئن، مضمون
26	assures	يضمن، يؤكد، يطمئن
27	assuring	طمأنة، مؤكد، مطمئن، ضمان، ضامن، تأكيد
28	attain	يحقق، يحرز، ينال
29	attained	محقق، أحرز، نال، حقق
30	attaining	إحراز، ينال، أَحْرَز
31	attainment	إنجاز
32	attains	يحقق، يحرز، ينال
33	attractive	جذاب، مغري، جاذب، ملفت
34	attractiveness	جاذبية
35	beautiful	جميل
36	beautifully	بطريقة رائعة، بصورة رائعة، بشكل رائع، بشكل جميل، بصورة جميلة، بطريقة جميلة، بنحو جميل، على نحو رائع

No.	English Word	Arabic Translation
37	beneficially	بشكل مفيد، بصورة مفيدة، بطريقة مفيدة، نحو مفيد، بشكل نافع، بصورة نافعة، بطريقة نافعة، بنحو نافع
38	benefited	انتفع، أفاد، مستفاد، استفاد
39	benefiting	مُستَفِيد، انتفاع، استفادة
40	benefitted	استفاد، أفاد، مستفاد، أنتفع
41	benefitting	مُستَفِيد، انتفاع، منفعة
42	best	أحسَن، أفضل
43	better	يحسن، أحسن، أفضل
44	bolsters	يسند، يدعم
45	bolstered	عزز، معزز، ساند
46	bolstering	تدعيم، يدعم، التعزيز، تقوية، يعزز
47	boom	مزدهرة، إزدهار، طفرة، انتعاش، ينتعش، يزدهر
48	booming	يزدهر، مزدهر، انتعاش، ازدهار
49	boost	تدعيم، يعزز، تحفيز، تعزيز، تقوية، يدعم، انتعاش
50	boosted	مدعوم، عزز
51	breakthrough	اكتشاف هام، اكتشاف مهم، إنجاز
52	brilliant	مشرق، باهِر، لامع
53	charitable	خيري، إحساني، إغاثي
54	collaborate	يتكاتف، يتعاون، يتضافر، تعاون
55	collaborated	تكاتف، تعاون، تضافر
56	collaborates	يتكاتف، يتعاون، يتضافر
57	collaborating	تعاون، تكاتف، يتعاون، يتكاتف
58	collaboration	تضافر، التآزر، تعاون
59	collaborative	تشاركي
60	collaborator	مُتَعَاوِن
61	compliment	إطراء، مديح، ثناء
62	complimentary	مجاملة، إطرائي، المجانية
63	complimented	جامل، مدح
64	complimenting	الثناء، مجاملة، يجامل، مدح، إطراء
65	conducive	مفيد، مؤات، مفضية، مشجعة
66	confident	واثق، جازم، موقن، ثقة
67	constructive	مفيد، بناء، هادف
68	constructively	بشكل بَنّاء، بصورة بناءه، بنحو بناء، بطريقة بناءه
69	courteous	مهذب، لبق، لطيف، راقي
70	creative	إبداعي، مبتكر، مبدع
71	creatively	بنحو مبدع، بشكل مبدع، بطريقة مبدعة، بشكل إبداعي، بصورة إبداعية، بطريقة إبداعية، بنحو إبداعي
72	creativeness	الإبداع
73	creativity	الإبداع
74	delight	سرور، بهجة، فرح، إسعاد
75	delighted	مسرور، سعيد، فرح، مبتهج
76	delightful	مسرور، سعيد، مفرح
77	delightfully	بشكل مفرح، بصورة مفرحة، بنحو مفرح
78	delighting	مبهج، ابتهاج
79	dependability	جدارة، موثوقيّة
80	dependable	مَوْثُوق
81	desirable	مستحسن، مستحب، جذاب، مرغوب، منشود
82	desired	مستهدف، مرغوب، مفضل، منشود، مرجوة
83	despite	رغم أن، على الرغم، بالرغم من، رغم
84	diligent	دؤوب، مجد، مجتهد، حثيث
85	diligently	بشكل مجتهد، بصورة مجتهدة، بطريقة مجتهدة، بنحو مجد، بشكل مستمر، بصورة مستمرة، بطريقة مستمرة، بنحو مستمر

No.	English Word	Arabic Translation
86	distinction	التفوق، الامتياز، التفرد، التميز
87	distinctive	مميز، متميز، لافت، فريد
88	distinctively	،بصورة لافته، بطريقة لافتة، بشكل لافت، بنحو لافت، بصفة مميزة، بشكل مميز ،بطريقة مميزة، بصورة مميزة، بنحو مميز، بشكل فريد، بصورة فريدة، بطريقة فريدة بنحو فريد
89	distinctiveness	التفوق، التميز
90	dream	الحلم
91	easier	أيسر، أسهل
92	easily	،بشكل سلس، بصورة سلسة، بنحو سلس، بطريقة سلسة، بنحو يسير، بشكل يسير بصورة يسيرة، بطريقة يسيرة، بشكل مريح، بصورة مريحة، بطريقة مريحة، بنحو مريح، بشكل سهل، بصورة سهلة، بطريقة سهلة، بنحو سهل
93	easy	بسيط، يسير، هين، سهل، مريح
94	efficiency	الكفاءة، الفعالية
95	efficient	فعال، كفء
96	efficiently	بشكل فعال، بصورة فعالة، نحو فعال، بطريقة فعالة، بشكل مقتدر، بنحو مقتدر، بطريقة مقتدرة، بصورة مقتدرة
97	empower	يمكن، تمكين
98	empowered	مكن
99	empowering	يمكن، تمكين
100	empowers	يمكن
101	enable	يتيح، يمكن، تمكين
102	enabled	مكن، أتاح
103	enables	يمكن، يمكن، يتيح
104	enabling	تمكين، يمكن
105	encouraged	شجع، حث، دعم
106	encouragement	تشجيع، تحفيز، دعم
107	encourages	يشجع، يحفز، يحث، يدعم
108	encouraging	مشجعة، تشجيع، يشجع، داعم، يحفز، يدعم
109	enhance	يقوي، يعزز، يحسن
110	enhanced	قوى، عزز، حسن
111	enhancement	التطوير، التعزيز، التحسين
112	enhances	يحسن، يطور، يقوي، يعزز
113	enhancing	تطوير، تعزيز، معزز، يطور، يعزز، يقوي، تحسين
114	enjoy	يتمتع، يستمتع
115	enjoyable	مبهج، ممتع، سارّ
116	enjoyably	،بصورة ممتعة، بشكل ممتع، بطريقة ممتعة، بنحو ممتع، بصورة سارة، بشكل سارّ بنحو سارّ، بطريقة سارة
117	enjoyed	تمتع، حظي، استمتع، ممتع
118	enjoying	استمتاع، يتمتع، ممتع، مستمتع، تمتع
119	enjoyment	استمتاع، ممتع، تمتع
120	enjoys	يتمتع، يستمتع
121	enthusiasm	شغف، تحمس، حيوية، حماس
122	enthusiastic	نشيط، شغوف، متحمس، حماسي
123	enthusiastically	بصورة حماسية، بشكل حماسي، بطريقة حماسية، نحو حماسي، بصورة شغوفة، بطريقة شغوفة، نحو شغوف، بشكل شغوف
124	excellence	الامتياز، التفوق
125	excellent	متقن، رائع، المتميز، ممتاز
126	excelling	يتميز، ابداع
127	excels	يبرع، يتميز، يتألق، يتفوق، يبرز، يفوق
128	exceptional	فائق، استثنائي، مُتميز
129	exceptionally	،بصورة استثنائية، بشكل استثنائي، بطريقة استثائية، بنحو استثنائي، بطريقة متميزة بنحو متميز، بشكل متميز، بصورة مميزة

No.	English Word	Arabic Translation
130	excited	متحمس، متشوق
131	excitement	التشويق، الحماس
132	exciting	مشوق، مثيرة، مثير، مشجع
133	exclusive	حصري، استثنائي
134	exclusively	بشكل حصري، بطريقة حصرية، بصورة حصرية، بنحو حصري، حصري
135	exclusiveness	التفرد
136	exclusivity	الحصرية، الانفراد، التفرد
137	exemplary	نموذجي، مثالي
138	fantastic	رائع، مذهل
139	favorable	مفضل
140	favorably	بشكل إيجابي، بصورة إيجابية، بنحو إيجابي، بطريقة إيجابية
141	favored	محبذ، مستحسن، مفضل
142	favoring	تفضيل، يفضل
143	favorite	مفضل
144	friendly	ودي، بشكل ودي، بصورة ودية، بنحو ودي، بطريقة ودية
145	gain	يكتسب، يكسب، مكسب، الكسب، يجني
146	gained	اكتسب، كسب، مكتسب، جنى
147	gaining	يكتسب، يكسب، مكتسب، مكسب، يجني، كسب
148	good	الجيد
149	greatest	الأعظم
150	greatly	قدر كبير، إلى حد كبير، بشكل كبير، بنحو كبير، بصورة كبيرة
151	greatness	المجد، العظمة
152	happiest	الأمتع، الأسعد
153	happily	بصورة سعيدة، بشكل سعيد، بطريقة سعيدة، بنحو سعيد
154	happiness	البهجة، السعادة، الفرح، الهناء، السرور
155	happy	سعيد، فرح، مسرور، مبتهج
156	highest	قصوى، الأقصى، الأعلى
157	honor	الشرف، الفخر
158	honored	مشرف، يكرم، شرف
159	honoring	تشريف، تكريم
160	ideal	مثالي
161	impress	يبهر
162	impressed	مندهش، معجب
163	impressing	مثير للإعجاب، ملفت، مبهر
164	impressive	مذهل، مدهش، مبهر، رائع
165	impressively	بشكل مثير للإعجاب، بصورة مثير للإعجاب، بطريقة مثير للإعجاب، بنحو مثير للإعجاب، بشكل مذهل، بصورة مذهلة، بنحو مذهل، بطريقة مذهلة، بشكل ملفت، بصورة ملفتة، بطريقة ملفتة، بنحو ملفت، بطريقة مبهرة، بصورة مبهرة، بنحو مبهر، بشكل مبهر
166	improve	يطور، يحسن، يتحسن
167	improved	محسنة، التحسن، حسن، متحسن، متطور
168	improvement	تطوير، إصلاحات، تحسين
169	improves	يُحسِّن، يتحسن، يطور
170	improving	تطوير، التحسن، يطور، يُحسِّن
171	incredible	مذهل، مدهش، رائع
172	incredibly	بنحو رائع، بطريقة رائعة، بصورة رائعة، بشكل رائع، بشكل مذهل، بصورة مذهلة، بنحو مذهل، بطريقة مذهلة، بصورة مدهشة، بنحو مدهش، بشكل مدهش، بطريقة مدهشة
173	influential	فعال
174	informative	مفيد، غني بالمعلومات
175	ingenuity	الإبداع، البراعة، العبقرية
176	innovate	يبتكر، يخترع
177	innovated	مبتكر، مخترع

No.	English Word	Arabic Translation
178	innovates	يبتكر، يخترع
179	innovating	الابتكار، الأختراع، يبتكر، يخترع
180	innovation	الابتكار، الأختراع
181	innovative	إبداعي، ابتكاري
182	innovativeness	الابتكار، الإبداع
183	innovator	مبتكر، مخترع
184	insightful	متبصر
185	inspiration	إلْهام، تحفيز
186	inspirational	مُلهم
187	integrity	النزاهة، الأمانة
188	invent	يبتكر، يخترع
189	invented	ابتكر، اخترع
190	inventing	الاختراع، الابتكار، يخترع، يبتكر
191	invention	الابتكار، الاختراع
192	inventive	إبداعي، ابتكاري
193	inventiveness	الابتكار، الإبداع
194	inventor	مبتكر، مخترع
195	leadership	الريادة، القيادة
196	leading	متقدم، رائد، قيادي
197	loyal	ولاء، مخلص
198	lucrative	مربح، مجزي، مثمر، مدر
199	meritorious	جدير
200	opportunity	فرصة
201	optimistic	إيجابي، متفائل
202	outperform	يتفوق، يتجاوز
203	outperformed	يتفوق، جاوز
204	outperforming	جاوز، يتفوق
205	outperforms	يتجاوز
206	perfect	مثالي، ممتاز
207	perfected	أتقن
208	perfectly	بشكل متقن، بشكل مثالي، أكمل وجه
209	pleasant	ممتع، مبهج، سارّ
210	pleasantly	بنحو سارّ، بشكل سارّ، بكل سرور، بشكل لطيف
211	pleased	سعيد، مسرور
212	pleasure	السرور
213	plentiful	وفير، وافر
214	popular	شائع، رائج، مشهور
215	popularity	رواج، شعبية، الشهرة، انتشار
216	positive	جيد، إيجابي
217	positively	،بشكل إيجابي، نحو إيجابي، نحو إيجابي، صوره ايجابيه، بطريقة إيجابية، بشكل جيد بصورة جيدة، بنحو جيد، بطريقة جيدة
218	preeminence	امتياز، الأسبقية، التفوق
219	preeminent	رائد، متميز، بارز
220	premier	رائد
221	premiere	رائد
222	prestige	مرموق
223	prestigious	فخم، راقي، مرموق، عريق
224	proactive	نشط
225	proactively	بصورة استباقية، بشكل استباقي، بطريقة استباقية، بنحو استباقي
226	proficiency	إجادة، براعة، إتقان، كفاءة
227	proficient	ماهر، بارع، متقن، متمكن

No.	English Word	Arabic Translation
228	proficiently	بشكل ماهر، بصورة ماهرة، بطريقة ماهرة، بنحو ماهر، بشكل متقن، بصورة متقنة، بطريقة متقنة، بنحو متقن، بصورة بارعة، بطريقة بارعة، بشكل متمكن، بصورة متمكنة، بطريقة متمكنة
229	profitability	ربحية
230	profitable	مربح، مثمر
231	profitably	بصورة مربحة، بشكل مربح، بنحو مربح، بطريقة مربحة
232	progress	تقدم، نمو، تطور، انجاز، يتقدم، يتطور، ينجز، ينمو
233	progressed	تقدم، متقدم، متطور، يتقدم، متقدم
234	progressing	متقدم، يتطور، يتقدم، متطور
235	prospered	ازدهر
236	prospering	يزدهر
237	prosperity	رخاء، ازدهار، رفاه
238	prosperous	مزدهر
239	prospers	يزدهر
240	rebound	يتعافى، ينتعش
241	rebounded	تعافى، انتعش
242	rebounding	التعافي
243	receptive	منفتح
244	regain	يستعيد، يسترجع
245	regained	استرجع، استعاد
246	regaining	استعادة، يسترجع
247	resolve	حل
248	revolutionize	يحدث ثورة
249	revolutionized	أحدث ثورة
250	revolutionizes	يحدث ثورة
251	revolutionizing	إحداث ثورة، يحدث ثورة
252	reward	يكافئ، جائزة
253	rewarded	كافأ
254	rewarding	مجزي
255	satisfaction	الرضى، الارتياح
256	satisfactorily	بشكل مرضي، بنحو مرضي، بصورة مرضية، بطريقة مرضية
257	satisfactory	مُرْضِي، مقنع
258	satisfied	مكتفي، مُرْضِي، مقتنع، راضي
259	satisfies	يستوفي، يشبع، يلبي، يرضي
260	satisfy	يستوفي، يشبع، يلبي، يرضي
261	satisfying	مُرْضِي، مقنع
262	smooth	منتظم، متجانسة، سلس
263	smoothing	يسهل
264	smoothly	بشكل سلس، بنحو سلس، بطريقة سلسة، بصورة سلسة
265	solves	يحلّ
266	solving	حل
267	spectacular	مذهل، مدهش، رائع، مبهر
268	spectacularly	بصورة مذهلة، بشكل مذهل، بنحو مذهل، بطريقة مذهلة، بطريقة مدهشة، بشكل مدهش، بصورة مدهشة، بنحو مدهش
269	stability	الاستقرار
270	stabilization	الاستقرار
271	stabilize	يرسخ
272	stabilized	مستقر، راسخ
273	stabilizes	يرسخ
274	stabilizing	الاستقرار، يرسخ
275	stable	مستقر، متين، راسخ
276	strength	قدرة، قوة، متانة

No.	English Word	Arabic Translation
277	strengthen	يدعم، يقوي، يعزز، يمتن، يوطد
278	strengthened	دعم، معزز، عزز
279	strengthening	تمتين، التعزيز، تدعيم، توطيد، تعزيز
280	strengthens	يدعم، يقوي، يعزز
281	strong	متين، راسخ، قوي
282	stronger	أقوى
283	strongest	الأقوى
284	succeed	ينجح، النجاح
285	succeeded	ينجح
286	succeeding	النجاح، ينجح، يجتاز
287	succeeds	ينجح
288	success	النجاح، إنجاز
289	successful	ناجح
290	successfully	بشكل ناجح، بصورة ناجحة، بطريقة ناجحة، بنحو ناجح
291	superior	فائق، متفوق
292	surpass	يفوق، يتجاوز، يتفوق
293	surpassed	فاق، تجاوز
294	surpasses	يتخطى، يفوق، يتجاوز
295	surpassing	متفوق، تفوق، متجاوز، يتجاوز
296	transparency	النزاهة، الشفافية
297	tremendous	هائل، ضخمة
298	tremendously	بنحو هائل، بصورة هائلة، بشكل هائل، بطريقة هائلة
299	unmatched	لا تضاهى، فذ، لا مثيل له، لا نظير لها، فريد
300	unparalleled	لا تضاهى، ليس لها مثيل، لا مثيل له، غير مسبوق، لا نظير لها، منقطع النظير، فريد، لا مثيل لها
301	unsurpassed	لا نظير لهما، فريد من نوعه، لا نظير له، لا تضاهى، لا مثيل له
302	upturn	تحسن، تقدم، التحسن، انتعاش
303	valuable	ثمين
304	versatile	مرن
305	versatility	مرونة
306	vibrancy	حيوية
307	vibrant	حيوي
308	win	يفوز، الفوز، ينتصر، الأنتصار
309	winner	المنتصر، الفائز
310	winning	الفوز، يفوز
311	worthy	جدير

Table A1. (a-2) Positive English to Lemmatized Arabic Translation (*N =980*)

No.	English Word	Arabic Translation
1	able	قادِر
2	abundance	وَفْرَة، غَزارَة
3	abundant	وَفْرَة، غَزِير، وَفِير، وافِر، زاخِر
4	acclaimed	مَرْمُوق، مَشْهُود لِ
5	accomplish	أَنْجَز، حَقَّق، إِنْجاز، أَحْرَز
6	accomplished	أَحْرَز، أَنْجَز، إِنْجاز، حَقَّق
7	accomplishes	أَنْجَز، حَقَّق، أَحْرَز
8	accomplishing	أَنْجَز، حَقَّق، أَحْرَز، إِنْجاز
9	accomplishment	إِنْجاز، مُنْجَز
10	achieve	أَنْجَز، حَقَّق، أَحْرَز
11	achieved	أَنْجَز، حَقَّق، مُحْرِز، مُحَقَّق، أَحْرَز
12	achievement	إِنْجاز، مُنْجَز
13	achieves	أَنْجَز، حَقَّق، أَحْرَز
14	achieving	أَنْجَز، أَحْرَز، تَحْقِيق، إِنْجاز، حَقَّق
15	adequately	،شَكْل مُلائِم، صُورَة مُلائِم، طَرِيقَة مُلائِم، نَحْو مُلائِم، نَحْو كافِي، شَكْل كافِي، طَرِيقَة كافِي صُورَة كافِي
16	advances	تَقَدُّم، تَقَدَّم
17	advancement	تَطَوُّر، تَقَدُّم
18	advancing	تَطْوِير، تَقَدُّم، تَقَدَّم
19	advantage	مَزِيَّة، تَفَوُّق، مِيزَة، أَفْضَلِيَّة، مِيزَة
20	advantaged	مُمَيَّز، مِيزَة
21	advantageous	مَوات، نافِع، مُفِيد
22	advantageously	شَكْل مُفِيد، صُورَة مُفِيد، طَرِيقَة مُفِيد، نَحْو مُفِيد، عَلَى شَكْل مُفِيد، عَلَى نَحْو مُفِيد، عَلَى طَرِيقَة مُفِيد، شَكْل نافِع، صُورَة نافِع، نَحْو نافِع، طَرِيقَة نافِع
23	alliance	تَحالُف، اِئْتِلاف، اِتِّحاد، حِلْف
24	assure	طَمْأَنَة، ضَمِن، أَكَّد، أَمَّن، طَمْأَن
25	assured	ضَمِن، أَكَّد، طَمْأَن، مُؤَكَّد، مُطْمَئِنّ، مَضْمُون
26	assures	ضَمِن، أَكَّد، طَمْأَن
27	assuring	طَمْأَنَة، مُؤَكِّد، مُطْمَئِنّ، ضَمان، ضامِن، تَأْكِيد
28	attain	حَقَّق، أَحْرَز، نال
29	attained	مُحَقَّق، أَحْرَز، نال، حَقَّق
30	attaining	إِحْراز، نال، أَحْرَز
31	attainment	إِنْجاز
32	attains	حَقَّق، أَحْرَز، نال
33	attractive	جَذّاب، مُغْرِي، جاذِب، مُلْفِت
34	attractiveness	جاذِبِيَّة
35	beautiful	جَمِيل
36	beautifully	طَرِيقَة رائِع، صُورَة رائِع، شَكْل رائِع، شَكْل جَمِيل، صُورَة جَمِيل، طَرِيقَة جَمِيل، نَحْو جَمِيل، عَلَى نَحْو رائِع
37	beneficially	شَكْل مُفِيد، صُورَة مُفِيد، طَرِيقَة مُفِيد، نَحْو مُفِيد، شَكْل نافِع، صُورَة نافِع، طَرِيقَة نافِع، نَحْو نافِع
38	benefited	اِنْتَفَع، أَفاد، مُسْتَفاد، اِسْتَفاد
39	benefiting	مُسْتَفِيد، اِنْتِفاع، اِسْتِفادَة
40	benefitted	اِسْتَفاد، أَفاد، مُسْتَفاد، اِنْتَفَع
41	benefitting	مُسْتَفِيد، اِنْتِفاع، مَنْفَعَة
42	best	أَحْسَن، أَفْضَل
43	better	حَسَّن، أَحْسَن، أَفْضَل
44	bolsters	أَسْنَد، دَعَّم
45	bolstered	عَزَّز، مُعَزِّز، سانَد
46	bolstering	تَدْعِيم، دَعَّم، تَعْزِيز، تَقْوِيَة، عَزَّز

No.	English Word	Arabic Translation
47	boom	مُزْدَهِر، اِزْدِهار، طَفْرَة، اِنْتِعاش، اِنْتَعَش، اِزْدَهَر
48	booming	اِزْدَهَر، مُزْدَهِر، اِنْتِعاش، اِزْدِهار
49	boost	تَدْعِيم، عَزَّز، تحفيز، تَعْزِيز، تَقْوِيَة، دَعَّم، اِنْتِعاش
50	boosted	مَدْعُوم، عَزَّز
51	breakthrough	اِكْتِشاف هامّ، اِكْتِشاف مُهِمّ، إِنْجاز
52	brilliant	مَشْرِق، باهِر، لامِع
53	charitable	خَيْرِيّ، إِحْساني، اغاثي
54	collaborate	تَكاتَف، تَعاوَن، تَضافَر، تَعاوُن
55	collaborated	تَكاتُف، تَعاوُن، تَضافُر
56	collaborates	تَكاتَف، تَعاوَن، تَضافَر
57	collaborating	تَعاوُن، تَكاتُف، تَعاوَن، تَكاتَف
58	collaboration	تَضافُر، تَآزُر، تَعاوُن
59	collaborative	شارَك
60	collaborator	مُتَعاوِن
61	compliment	إِطْراء، مَدِيح، ثَناء
62	complimentary	مُجامَلَة، إِطْراء، مَجّانِيّ
63	complimented	جامَل، مَدْح
64	complimenting	ثَناء، مُجامَلَة، جامَل، مَدْح، إِطْراء
65	conducive	مُفِيد، مُؤاتِي، مِفَضّ، مُشَجِّع
66	confident	واثِق، جازِم، مُوقِن، ثِقَة
67	constructive	مُفِيد، بَنّاء، هادِف
68	constructively	شَكْل بَنّاء، صُورَة بَنّاء، نَحْو بَنّاء، طَرِيقَة بَنّاء
69	courteous	مُهَذّب، لَبِق، لَطِيف، راقِي
70	creative	إِبْداع، مُبْتَكَر، مُبْدِع
71	creatively	نَحْو مُبْدِع، شَكْل مُبْدِع، طَرِيقَة مُبْدِع، شَكْل إِبْداع، صُورَة إِبْداع، طَرِيقَة إِبْداع، نَحْو إِبْداع
72	creativeness	إِبْداع
73	creativity	إِبْداع
74	delight	سُرُور، بَهِج، فَرَح، اسعاد
75	delighted	مَسْرُور، سَعِيد، فَرَح، مُبْتَهِج
76	delightful	مَسْرُور، سَعِيد، مُفْرِح
77	delightfully	شَكْل مُفْرِح، صُورَة مُفْرِح، نَحْو مُفْرِح
78	delighting	مُبْهِج، اِبْتِهاج
79	dependability	جَدارَة، مَوْثُوق
80	dependable	مَوْثُوق
81	desirable	مُسْتَحْسَن، مُسْتَحَبّ، جَذّاب، مَرْغُوب، مَنْشُود
82	desired	مُسْتَهْدَف، مَرْغُوب، مُفَضَّل، مَنْشُود، مَرْجُوّ
83	despite	رَغْم أَنَّ، عَلَى رَغْم، رَغْم مِن، رَغْم
84	diligent	دَءُوب، مَجْد، مُجْتَهِد، حَثِيث
85	diligently	،شَكْل مُجْتَهِد، صُورَة مُجْتَهِد، طَرِيقَة مُجْتَهِد، نَحْو مَجْد، شَكْل مُسْتَمِرّ، صُورَة مُسْتَمِرّ طَرِيقَة مُسْتَمِرّ، نَحْو مُسْتَمِرّ
86	distinction	تَفَوُّق، اِمْتِياز، تَفَرُّد، تَمَيُّز
87	distinctive	مُمَيَّز، مُتَمَيِّز، لافِت، فَرِيد
88	distinctively	صُورَة لافِت، طَرِيقَة لافِت، شَكْل لافِت، نَحْو لافِت، صِفَة مُمَيَّز، شَكْل مُمَيَّز، طَرِيقَة مُمَيَّز، صُورَة مُمَيَّز، نَحْو مُمَيَّز، شَكْل فَرِيد، صُورَة فَرِيد، طَرِيقَة فَرِيد، نَحْو فَرِيد
89	distinctiveness	تَفَوُّق، تَمَيُّز
90	dream	حُلْم
91	easier	أَيْسَر، أَسْهَل
92	easily	شَكْل سَلِس، صُورَة سَلِس، نَحْو سَلِس، طَرِيقَة سَلِس، نَحْو يَسِير، شَكْل يَسِير، صُورَة ،يَسِير، طَرِيقَة يَسِير، شَكْل مُرِيح، صُورَة مُرِيح، طَرِيقَة مُرِيح، نَحْو مُرِيح، شَكْل سَهْل صُورَة سَهْل، طَرِيقَة سَهْل، نَحْو سَهْل
93	easy	بَسِيط، يَسِير، هَيِّن، سَهْل، مُرِيح
94	efficiency	كَفاءَة، فَعّالِيَّة

No.	English Word	Arabic Translation
95	efficient	فَعّال، كَفْء
96	efficiently	شَكْل فَعّال، صُورَة فَعّال، نَحْو فَعّال، طَرِيقَة فَعّال، شَكْل مُقْتَدِر، نَحْو مُقْتَدِر، طَرِيقَة مُقْتَدِر، صُورَة مُقْتَدِر
97	empower	مَكَّن، تَمْكِين
98	empowered	مَكَّن
99	empowering	مَكَّن، تَمْكِين
100	empowers	مَكَّن
101	enable	أتاح، مَكَّن، تَمْكِين
102	enabled	مَكَّن، أتاح
103	enables	مَكَّن، مَكَّن، أتاح
104	enabling	تَمْكِين، مَكَّن
105	encouraged	شَجَّع، حَثّ، دَعْم
106	encouragement	تَشْجِيع، تحفيز، دَعْم
107	encourages	شَجَّع، حَفَز، حَثّ، دَعَّم
108	encouraging	مُشَجِّع، تَشْجِيع، شَجَّع، داعِم، حَفَز، دَعَّم
109	enhance	قَوَّى، عَزَّز، حَسَّن
110	enhanced	قَوَّى، عَزَّز، حَسَّن
111	enhancement	تَطْوِير، تَعْزِيز، تَحْسِين
112	enhances	حَسَّن، طَوَّر، قَوَّى، عَزَّز
113	enhancing	تَطْوِير، تَعْزِيز، مُعَزِّز، طَوَّر، عَزَّز، قَوَّى، تَحْسِين
114	enjoy	تَمَتَّع، اِسْتَمْتَع
115	enjoyable	مُبْهِج، مُمْتِع، سارّ
116	enjoyably	صُورَة مُمْتِع، شَكْل مُمْتِع، طَرِيقَة مُمْتِع، نَحْو مُمْتِع، صُورَة سارّ، شَكْل سارّ، نَحْو سارّ، طَرِيقَة سارّ
117	enjoyed	تَمَتَّع، حَظِي، اِسْتَمْتَع، مُمْتِع
118	enjoying	اِسْتِمْتاع، تَمَتُّع، مُمْتِع، مستمتع، تَمَتَّع
119	enjoyment	اِسْتِمْتاع، مُمْتِع، تَمَتُّع
120	enjoys	تَمَتَّع، اِسْتَمْتَع
121	enthusiasm	شَغَف، تَحَمُّس، حَيَوِيَّة، حَماس
122	enthusiastic	نَشِيط، شَغُوف، مُتَحَمِّس، حَماس
123	enthusiastically	صُورَة حَماسِيّ، شَكْل حَماس، طَرِيقَة حَماسِيّ، نَحْو حَماس، صُورَة شَغُوف، طَرِيقَة شَغُوف، نَحْو شَغُوف، شَكْل شَغُوف
124	excellence	اِمْتِياز، تَفَوُّق
125	excellent	مُتْقَن، رائِع، مُتَمَيِّز، مُمْتاز
126	excelling	تَمَيُّز، إِبْداع
127	excels	بَرَع، تَمَيَّز، تَأَلَّق، تَفَوَّق، بَرَز، فاق
128	exceptional	فائِق، اِسْتِثْنائِيّ، مُتَمَيِّز
129	exceptionally	صُورَة اِسْتِثْنائِيّ، شَكْل اِسْتِثْنائِيّ، طَرِيقَة استثنائيه، نَحْو اِسْتِثْنائِيّ، طَرِيقَة مُتَمَيِّز، نَحْو مُتَمَيِّز، شَكْل مُتَمَيِّز، صُورَة مُمَيِّز
130	excited	مُتَحَمِّس، متشوق
131	excitement	تَشْوِيق، حَماس
132	exciting	مُشَوِّق، مُثِير، مُثِير، مُشَجِّع
133	exclusive	حَصْرِيّ، اِسْتِثْنائِيّ
134	exclusively	شَكْل حَصْرِيّ، طَرِيقَة حَصْرِيّ، صُورَة حَصْرِيّ، نَحْو حَصْرِيّ، حَصْرِيّ
135	exclusiveness	تَفَرُّد
136	exclusivity	حَصْرِيّ، اِنْفِراد، تَفَرُّد
137	exemplary	نَمُوذَجِيّ، مِثالِيّ
138	fantastic	رائِع، مُذْهِل
139	favorable	مُفَضَّل
140	favorably	شَكْل إِيجابِيّ، صُورَة إِيجابِيّ، نَحْو إِيجابِيّ، طَرِيقَة إِيجابِيّ
141	favored	محبذ، مُسْتَحْسَن، مُفَضَّل
142	favoring	تَفْضِيل، فَضَّل

No.	English Word	Arabic Translation
143	favorite	مُفَضَّل
144	friendly	وُدِّيّ، شَكْل وُدِّيّ، صُورَة وُدِّيّ، نَحْو وُدِّيّ، طَرِيقَة وُدِّيّ
145	gain	اِكْتَسَب، كَسَب، مَكْسَب، كَسْب، جَنَى
146	gained	اِكْتَسَب، كَسْب، مُكْتَسَب، جَنَى
147	gaining	اِكْتَسَب، كَسَب، مُكْتَسَب، مَكْسَب، جَنَى، كَسْب
148	good	جَيِّد
149	greatest	أَعْظَم
150	greatly	قَدْر كَبِير، إِلَى حَدّ كَبِير، شَكْل كَبِير، نَحْو كَبِير، صُورَة كَبِير
151	greatness	مَجْد، عَظْمَة
152	happiest	أَمْتَع، أَسْعَد
153	happily	صُورَة سَعِيد، شَكْل سَعِيد، طَرِيقَة سَعِيد، نَحْو سَعِيد
154	happiness	بَهِج، سَعادَة، فَرَح، هَناء، سُرُور
155	happy	سَعِيد، فَرَح، مَسْرُور، مُبْتَهِج
156	highest	أَقْصَى، أَقْصَى، أَعْلَى
157	honor	شَرَف، فَخْر
158	honored	مُشَرِّف، كَرَّم، شَرَف
159	honoring	تَشْرِيف، تَكْرِيم
160	ideal	مِثالِيّ
161	impress	بَهَر
162	impressed	مُنْدَهِش، مُعْجَب
163	impressing	مُثِير إِعْجاب، مُلْفِت، مبهر
164	impressive	مُذْهِل، مُدْهِش، مبهر، رائِع
165	impressively	شَكْل مُثِير إِعْجاب، صُورَة مُثِير إِعْجاب، طَرِيقَة مُثِير إِعْجاب، نَحْو مُثِير إِعْجاب، شَكْل مُذْهِل، صُورَة مُذْهِل، نَحْو مُذْهِل، طَرِيقَة مُذْهِل، شَكْل مُلْفِت، صُورَة مُلْفِت، طَرِيقَة مُلْفِت، نَحْو مُلْفِت، طَرِيقَة مبهره، صُورَة مبهره، نَحْو مبهر، شَكْل مبهر
166	improve	طَوَّر، حَسَّن، تَحَسَّن
167	improved	مُحَسِّن، تَحَسُّن، حَسَّن، متحسن، مُتَطَوِّر
168	improvement	تَطْوِير، إِصْلاحات، تَحْسِين
169	improves	حَسَّن، تَحَسَّن، طَوَّر
170	improving	تَطْوِير، تَحَسُّن، طَوَّر، حَسَّن
171	incredible	مُذْهِل، مُدْهِش، رائِع
172	incredibly	نَحْو رائِع، طَرِيقَة رائِع، صُورَة رائِع، شَكْل رائِع، شَكْل مُذْهِل، صُورَة مُذْهِل، نَحْو مُذْهِل، طَرِيقَة مُذْهِل، صُورَة مُدْهِش، نَحْو مُدْهِش، شَكْل مُدْهِش، طَرِيقَة مُدْهِش
173	influential	فَعّال
174	informative	مُفِيد، غَنِيّ مَعْلُومَة
175	ingenuity	إِبْداع، بَراعَة، عَبْقَرِيَّة
176	innovate	اِبْتَكَر، اِخْتَرَع
177	innovated	مُبْتَكَر، مُخْتَرَع
178	innovates	اِبْتَكَر، اِخْتَرَع
179	innovating	اِبْتِكار، اِخْتِراع، اِبْتَكَر، اِخْتَرَع
180	innovation	اِبْتِكار، اِخْتِراع
181	innovative	إِبْداع، اِبْتِكارِيّ
182	innovativeness	اِبْتِكار، إِبْداع
183	innovator	مُبْتَكَر، مُخْتَرَع
184	insightful	مُتَبَصِّر
185	inspiration	إِلْهام، تحفيز
186	inspirational	مُلْهَم
187	integrity	نَزاهَة، أَمانَة
188	invent	اِبْتَكَر، اِخْتَرَع
189	invented	اِبْتَكَر، اِخْتَرَع
190	inventing	اِخْتِراع، اِبْتِكار، اِخْتَرَع، اِبْتَكَر
191	invention	اِبْتِكار، اِخْتِراع

No.	English Word	Arabic Translation
192	inventive	إِبْداع، اِبْتِكاريّ
193	inventiveness	اِبْتِكار، إِبْداع
194	inventor	مُبْتَكِر، مُخْتَرَع
195	leadership	رياده، قِيادَة
196	leading	مُتَقَدِّم، رائِد، قِيادِيّ
197	loyal	وَلاء، مُخْلِص
198	lucrative	مُرْبِح، مِجَزّ، مُثْمِر، مَدَر
199	meritorious	جَدِير
200	opportunity	فُرْصَة
201	optimistic	إِيجابِيّ، مُتَفائِل
202	outperform	تَفَوَّق، تَجاوَز
203	outperformed	تَفَوَّق، جاوَز
204	outperforming	جاوَز، تَفَوَّق
205	outperforms	تَجاوَز
206	perfect	مِثالِيّ، مُمْتاز
207	perfected	أَتْقَن
208	perfectly	شَكْل مُتْقِن، شَكْل مِثالِيّ، أَكْمَل وَجْه
209	pleasant	مُمْتِع، مُبْهِج، سارّ
210	pleasantly	نَحْو سارّ، شَكْل سارّ، كُلّ سُرُور، شَكْل لَطِيف
211	pleased	سَعِيد، مَسْرُور
212	pleasure	سُرُور
213	plentiful	وَفِير، وافِر
214	popular	شائِع، رائِج، مَشْهُور
215	popularity	رَواج، شَعْبِيّ، شُهْرَة، اِنْتِشار
216	positive	جَيِّد، إِيجابِيّ
217	positively	شَكْل إِيجابِيّ، نَحْو إِيجابِيّ، نَحْو إِيجابِيّ، صُورَة إِيجابِيّ، طَرِيقَة إِيجابِيّ، شَكْل جَيِّد، صُورَة جَيِّد، نَحْو جَيِّد، طَرِيقَة جَيِّد
218	preeminence	اِمْتِياز، أَسْبَقِيَّة، تَفَوُّق
219	preeminent	رائِد، مُتَمَيِّز، بارِز
220	premier	رائِد
221	premiere	رائِد
222	prestige	مَرْمُوق
223	prestigious	فَخْم، راقِي، مَرْمُوق، عَرِيق
224	proactive	نَشِط
225	proactively	صُورَة اِسْتِباقِيّ، شَكْل اِسْتِباق، طَرِيقَة اِسْتِباقِيّ، نَحْو اِسْتِباق
226	proficiency	إِجادَة، بَراعَة، إِتْقان، كَفاءَة
227	proficient	ماهِر، بارِع، مُتْقِن، مُتَمَكِّن
228	proficiently	شَكْل ماهِر، صُورَة ماهِر، طَرِيقَة ماهِر، نَحْو ماهِر، شَكْل مُتْقِن، صُورَة مُتْقِن، طَرِيقَة مُتْقِن، نَحْو مُتْقِن، صُورَة بارِع، طَرِيقَة بارِع، شَكْل مُتَمَكِّن، صُورَة مُتَمَكِّن، طَرِيقَة مُتَمَكِّن
229	profitability	رِبْحِيّ
230	profitable	مُرْبِح، مُثْمِر
231	profitably	صُورَة مُرْبِح، شَكْل مُرْبِح، نَحْو مُرْبِح، طَرِيقَة مُرْبِح
232	progress	تَقَدَّم، نُمُوّ، تَطَوُّر، إِنْجاز، تَقَدَّم، تَطَوَّر، أَنْجَز، نَما
233	progressed	تَقَدَّم، مُتَقَدِّم، مُتَطَوِّر، تَقَدَّم، مُتَقَدِّم
234	progressing	مُتَقَدِّم، تَطَوَّر، تَقَدَّم، مُتَطَوِّر
235	prospered	اِزْدَهَر
236	prospering	اِزْدَهَر
237	prosperity	رَخاء، اِزْدِهار، رَفاه
238	prosperous	مُزْدَهِر
239	prospers	اِزْدَهَر
240	rebound	تَعافَى، اِنْتَعَش
241	rebounded	تَعافَى، اِنْتَعَش

No.	English Word	Arabic Translation
242	rebounding	تَعافِي
243	receptive	مُنْفَتِح
244	regain	اِسْتَعاد، اِسْتَرْجَع
245	regained	اِسْتَرْجَع، اِسْتَعاد
246	regaining	اِسْتِعادَة، اِسْتَرْجَع
247	resolve	حَلّ
248	revolutionize	حَدَث ثَوْرَة
249	revolutionized	أَحْدَث ثَوْرَة
250	revolutionizes	حَدَث ثَوْرَة
251	revolutionizing	إِحْداث ثَوْرَة، حَدَث ثَوْرَة
252	reward	كافَأ، جائِزَة
253	rewarded	كافَأ
254	rewarding	مُجَزّ
255	satisfaction	رِضَى، اِرْتِياح
256	satisfactorily	شَكْل مُرْضِي، نَحْو مُرْضِي، صُورَة مُرْضِي، طَرِيقَة مُرْضِي
257	satisfactory	مُرْضِي، مُقْنِع
258	satisfied	مُكْتَفِي، مُرْضِي، مُقْتَنِع، راضِي
259	satisfies	اِسْتَوْفَى، أَشْبَع، لَبَّى، أَرْضَى
260	satisfy	اِسْتَوْفَى، أَشْبَع، لَبَّى، أَرْضَى
261	satisfying	مُرْضِي، مُقْنِع
262	smooth	مُنْتَظِم، مُتَجانِس، سَلِس
263	smoothing	سَهَّل
264	smoothly	شَكْل سَلِس، نَحْو سَلِس، طَرِيقَة سَلِس، صُورَة سَلِس
265	solves	أَحَلّ
266	solving	حَلّ
267	spectacular	مُذْهِل، مُدْهِش، رائِع، مبهر
268	spectacularly	صُورَة مُذْهِل، شَكْل مُذْهِل، نَحْو مُذْهِل، طَرِيقَة مُذْهِل، طَرِيقَة مُدْهِش، شَكْل مُدْهِش، صُورَة مُدْهِش، نَحْو مُدْهِش
269	stability	اِسْتِقْرار
270	stabilization	اِسْتِقْرار
271	stabilize	رَسَّخ
272	stabilized	مُسْتَقِرّ، راسِخ
273	stabilizes	رَسَّخ
274	stabilizing	اِسْتِقْرار، رَسَّخ
275	stable	مُسْتَقِرّ، مَتِين، راسِخ
276	strength	قُدْرَة، قُوَّة، مَتانَة
277	strengthen	دَعَّم، قَوَّى، عَزَّز، مَتَّن، وَطَّد
278	strengthened	دَعْم، مُعَزّز، عَزَّز
279	strengthening	تَمْتِين، تَعْزِيز، تَدْعِيم، تَوْطِيد، تَعْزِيز
280	strengthens	دَعَّم، قَوَّى، عَزَّز
281	strong	مَتِين، راسِخ، قَوِيّ
282	stronger	أَقْوَى
283	strongest	أَقْوَى
284	succeed	نَجَح، نَجاح
285	succeeded	نَجَح
286	succeeding	نَجاح، نَجَح، اِجْتاز
287	succeeds	نَجَح
288	success	نَجاح، إِنْجاز
289	successful	ناجِح
290	successfully	شَكْل ناجِح، صُورَة ناحجه، طَرِيقَة ناجِح، نَحْو ناجِح
291	superior	فائِق، مُتَفَوِّق
292	surpass	فاق، تَجاوَز، تَفَوَّق

No.	English Word	Arabic Translation
293	surpassed	فاق، تَجاوُز
294	surpasses	تَخَطَّى، فاق، تَجاوَز
295	surpassing	مُتَفَوِّق، تَفَوُّق، مُتَجاوِز، تَجاوَز
296	transparency	نَزاهَة، شَفّافِيَّة
297	tremendous	هائِل، ضَخْم
298	tremendously	نَحْو هائِل، صُورَة هائِل، شَكْل هائِل، طَرِيقَة هائِل
299	unmatched	لا ضاهَى، فَذّ، لا مَثِيل لِ، لا نَظِير لِ، فَرِيد
300	unparalleled	لا ضاهَى، لَيس لِ مَثِيل، لا مَثِيل لِ، غَيْر مَسْبُوق، لا نَظِير لِ، مُنْقَطِع نَظِير، فَرِيد، لا مَثِيل لِ
301	unsurpassed	لا نَظِير لِ، فَرِيد مِن نَوْع، لا نَظِير لِ، لا ضاهَى، لا مَثِيل لِ
302	upturn	تَحَسُّن، تَقَدُّم، تَحَسُّن، اِنْتِعاش
303	valuable	ثَمِين
304	versatile	مَرِن
305	versatility	مُرُونَة
306	vibrancy	حَيَوِيَّة
307	vibrant	حَيَوِيّ
308	win	فاز، فَوْز، اِنْتَصَر، اِنْتِصار
309	winner	مُنْتَصِر، فائِز
310	winning	فَوْز، فاز
311	worthy	جَدِير

Table A1. (a-3.i) Positive Arabic One Word Dimensional (*N=355*)

No.	One Word Dimensional
1	أَتاح
2	أَتْقَن
3	أَحَلّ
4	أَحْرَز
5	أَحْسَن
6	أَرْضَى
7	أَسْبَقِيَّة
8	أَسْعَد
9	أَسْنَد
10	أَسْهَل
11	أَشْبَع
12	أَعْظَم
13	أَعْلَى
14	أَفاد
15	أَفْضَل
16	أَفْضَلِيَّة
17	أَقْصَى
18	أَقْوَى
19	أَكَّد
20	أَمانَة
21	أَمَّن
22	أَمْتَع
23	أَنْجَز
24	أَيْسَر
25	إِبْداع
26	إِتْقان
27	إِجادَة
28	إِحْراز
29	إِحْساني
30	إِصْلاحات
31	إِطْراء
32	إِلْهام
33	إِنْجاز
34	إِيجابِيّ
35	اسعاد
36	اغاثي
37	بارِز
38	بارِع
39	باهِر
40	بَراعَة
41	بَرَز
42	بَرَع
43	بَسِيط
44	بَنّاء
45	بَهَر
46	بَهِج
47	تحفيز
48	تَآزُر
49	تَأَلَّق
50	تَأْكِيد

No.	One Word Dimensional
51	تَجاوَز
52	تَجاوُز
53	تَحالُف
54	تَحَسَّن
55	تَحَسُّن
56	تَحَمَّس
57	تَحْسِين
58	تَحْقِيق
59	تَخَطَّى
60	تَدْعِيم
61	تَشْجِيع
62	تَشْرِيف
63	تَشْوِيق
64	تَضافَر
65	تَضافُر
66	تَطَوَّر
67	تَطَوُّر
68	تَطْوِير
69	تَعافَى
70	تَعافِي
71	تَعاوَن
72	تَعاوُن
73	تَعْزِيز
74	تَفَرُّد
75	تَفَوَّق
76	تَفَوُّق
77	تَفْضِيل
78	تَقَدَّم
79	تَقَدُّم
80	تَقْوِيَة
81	تَكاتَف
82	تَكاتُف
83	تَكْرِيم
84	تَمَتَّع
85	تَمَيَّز
86	تَمَيُّز
87	تَمْتِين
88	تَمْكِين
89	تَوْطِيد
90	ثَمِين
91	ثَناء
92	ثِقَة
93	جائِزَة
94	جاذِب
95	جاذِبِيَّة
96	جازِم
97	جامَل
98	جاوَز
99	جَدارَة
100	جَدِير
101	جَذّاب
102	جَمِيل

No.	One Word Dimensional
103	جَنَى
104	جَيِّد
105	حَثِيث
106	حَثّ
107	حَسَّن
108	حَصْرِيّ
109	حَظِي
110	حَفَز
111	حَقَّق
112	حَلّ
113	حَماس
114	حَيَوِيّ
115	حَيَوِيَّة
116	حُلْم
117	حِلْف
118	خَيْرِيّ
119	داعِم
120	دَءُوب
121	دَعَّم
122	دَعْم
123	رائِج
124	رائِد
125	رائِع
126	راسِخ
127	راضِي
128	راقِي
129	رياده
130	رَخاء
131	رَسَّخ
132	رَغْم
133	رَفاه
134	رَواج
135	رِبْحِيّ
136	رِضَى
137	زاخِر
138	سارّ
139	سانَد
140	سَعادَة
141	سَعِيد
142	سَلِس
143	سَهَّل
144	سَهْل
145	سُرُور
146	شائِع
147	شارَك
148	شَجَّع
149	شَرَف
150	شَعْبِيّ
151	شَغَف
152	شَغُوف
153	شَفّافِيَّة
154	شُهْرَة

No.	One Word Dimensional
155	ضامِن
156	ضَخْم
157	ضَمان
158	ضَمِن
159	طَفْرَة
160	طَمْأَن
161	طَمْأَنَة
162	طَوَّر
163	عَبْقَرِيَّة
164	عَرِيق
165	عَزَّز
166	عَظْمَة
167	غَزارَة
168	غَزِير
169	فائِز
170	فائِق
171	فاز
172	فاق
173	فَخْر
174	فَخْم
175	فَذّ
176	فَرَح
177	فَرِيد
178	فَضَّل
179	فَعّال
180	فَعّالِيَّة
181	فَوْز
182	فُرْصَة
183	قادِر
184	قَوِيّ
185	قَوَّى
186	قُدْرَة
187	قُوَّة
188	قِيادَة
189	قِيادِيّ
190	كافَأ
191	كَرَّم
192	كَسَب
193	كَسْب
194	كَفاءَة
195	كَفْء
196	لافِت
197	لامِع
198	لَبِق
199	لَبَّى
200	لَطِيف
201	ماهِر
202	مبهر
203	متحسن
204	متشوق
205	محبذ
206	مستمتع

No.	One Word Dimensional
207	مَتانَة
208	مَتِين
209	مَتْن
210	مَجّانِيّ
211	مَجْد
212	مَدَر
213	مَدِيح
214	مَدْح
215	مَدْعُوم
216	مَرِن
217	مَرْجُوّ
218	مَرْغُوب
219	مَرْمُوق
220	مَزِيَّة
221	مَسْرُور
222	مَشْرِق
223	مَشْهُور
224	مَضْمُون
225	مَكْن
226	مَكْسَب
227	مَنْشُود
228	مَنْفَعَة
229	مَوات
230	مَوْثُوق
231	مُؤاتِي
232	مُؤَكِّد
233	مُبْتَكَر
234	مُبْتَهِج
235	مُبْدِع
236	مُبْهِج
237	مُتَبَصِّر
238	مُتَجانِس
239	مُتَجاوِز
240	مُتَحَمِّس
241	مُتَطَوِّر
242	مُتَعاوِن
243	مُتَفائِل
244	مُتَفَوِّق
245	مُتَقَدِّم
246	مُتَمَكِّن
247	مُتَمَيِّز
248	مُتْقِن
249	مُثِير
250	مُثْمِر
251	مُجامَلَة
252	مُجْتَهِد
253	مُحَسِّن
254	مُحَقِّق
255	مُحْرِز
256	مُخْتَرَع
257	مُخْلِص
258	مُدْهِش

No.	One Word Dimensional
259	مُذْهِل
260	مُرُونَة
261	مُرِيح
262	مُرْبِح
263	مُرْضِي
264	مُزْدَهِر
265	مُسْتَحَبّ
266	مُسْتَحْسَن
267	مُسْتَفَاد
268	مُسْتَفِيد
269	مُسْتَقِرّ
270	مُسْتَهْدَف
271	مُشَجِّع
272	مُشَرِّف
273	مُشَوَّق
274	مُطْمَئِنّ
275	مُعَزِّز
276	مُعْجَب
277	مُغْرِي
278	مُفَضَّل
279	مُفِيد
280	مُفْرِح
281	مُقْتَنِع
282	مُقْنِع
283	مُكْتَسَب
284	مُكْتَفِي
285	مُلْفِت
286	مُلْهَم
287	مُمَيَّز
288	مُمْتاز
289	مُمْتِع
290	مُنْتَصِر
291	مُنْتَظِم
292	مُنْجَز
293	مُنْدَهِش
294	مُنْفَتِح
295	مُهَذّب
296	مُوقِن
297	مِثالِيّ
298	مِجَزّ
299	مِفَضّ
300	مِيزَة
301	ناجِح
302	نافِع
303	نال
304	نَجاح
305	نَجَح
306	نَزاهَة
307	نَشِط
308	نَشِيط
309	نَما
310	نَمُوذَجِيّ

No.	One Word Dimensional
311	نُمُوّ
312	هائِل
313	هادِف
314	هَناء
315	هَيِّن
316	واثِق
317	وافِر
318	وَطَّد
319	وَفِير
320	وَفْرَة
321	وَلاء
322	وُدِّيّ
323	يَسِير
324	ٱِئْتِلاف
325	ٱِبْتَكَر
326	ٱِبْتِكار
327	ٱِبْتِكارِيّ
328	ٱِبْتِهاج
329	ٱِتِّحاد
330	ٱِجْتاز
331	ٱِخْتَرَع
332	ٱِخْتِراع
333	ٱِرْتِياح
334	ٱِزْدَهَر
335	ٱِزْدِهار
336	ٱِسْتَرْجَع
337	ٱِسْتَعاد
338	ٱِسْتَفاد
339	ٱِسْتَمْتَع
340	ٱِسْتَوْفَى
341	ٱِسْتِثْنائِيّ
342	ٱِسْتِعادَة
343	ٱِسْتِفادَة
344	ٱِسْتِقْرار
345	ٱِسْتِمْتاع
346	ٱِكْتَسَب
347	ٱِمْتِياز
348	ٱِنْتَصَر
349	ٱِنْتَعَش
350	ٱِنْتَفَع
351	ٱِنْتِشار
352	ٱِنْتِصار
353	ٱِنْتِعاش
354	ٱِنْتِفاع
355	ٱِنْفِراد

Table A1. (a-3.ii) Positive Arabic Two Words Dimensional (*N=197*)

No.	Two Words Dimensional
1	أَحْدَث ثَوْرَة
2	أَكْمَل وَجْه
3	إِحْداث ثَوْرَة
4	حَدَث ثَوْرَة
5	رَغْم أَنَّ
6	رَغْم مِن
7	شَكْل إِبْداع
8	شَكْل إِيجابِيّ
9	شَكْل بَنّاء
10	شَكْل جَمِيل
11	شَكْل جَيِّد
12	شَكْل حَضْرِيّ
13	شَكْل حَماس
14	شَكْل رائِع
15	شَكْل سارّ
16	شَكْل سَعِيد
17	شَكْل سَلِس
18	شَكْل سَهْل
19	شَكْل شَغُوف
20	شَكْل فَرِيد
21	شَكْل فَعّال
22	شَكْل كافِي
23	شَكْل كَبِير
24	شَكْل لافِت
25	شَكْل لَطِيف
26	شَكْل ماهِر
27	شَكْل مبهر
28	شَكْل مُبْدِع
29	شَكْل مُتَمَكِّن
30	شَكْل مُتَمَيِّز
31	شَكْل مُتَّقِن
32	شَكْل مُجْتَهِد
33	شَكْل مُدْهِش
34	شَكْل مُذْهِل
35	شَكْل مُرِيح
36	شَكْل مُرْبِح
37	شَكْل مُرْضِي
38	شَكْل مُسْتَمِرّ
39	شَكْل مُفِيد
40	شَكْل مُفْرِح
41	شَكْل مُقْتَدِر
42	شَكْل مُلائِم
43	شَكْل مُلْفِت
44	شَكْل مُمَيَّز
45	شَكْل مُمْتِع
46	شَكْل مِثالِيّ
47	شَكْل ناجِح

No.	**Two Words Dimensional**
48	شَكْل نافِع
49	شَكْل هائِل
50	شَكْل وُدِّيّ
51	شَكْل يَسِير
52	شَكْل ٱسْتِباق
53	شَكْل ٱسْتِثْنائِيّ
54	صُورَة إِبْداع
55	صُورَة إِيجابِيّ
56	صُورَة بارِع
57	صُورَة بَنّاء
58	صُورَة جَمِيل
59	صُورَة جَيِّد
60	صُورَة حَصْرِيّ
61	صُورَة حَماسِيّ
62	صُورَة رائِع
63	صُورَة سارّ
64	صُورَة سَعِيد
65	صُورَة سَلِس
66	صُورَة سَهْل
67	صُورَة شَغُوف
68	صُورَة فَرِيد
69	صُورَة فَعّال
70	صُورَة كافِي
71	صُورَة كَبِير
72	صُورَة لافِت
73	صُورَة ماهِر
74	صُورَة مبهره
75	صُورَة مُتَمَكِّن
76	صُورَة مُتَّقِن
77	صُورَة مُجْتَهِد
78	صُورَة مُدْهِش
79	صُورَة مُذْهِل
80	صُورَة مُرِيح
81	صُورَة مُرْبِح
82	صُورَة مُرْضِي
83	صُورَة مُسْتَمِرّ
84	صُورَة مُفِيد
85	صُورَة مُفْرِح
86	صُورَة مُقْتَدِر
87	صُورَة مُلائِم
88	صُورَة مُلْفِت
89	صُورَة مُمَيَّز
90	صُورَة مُمْتِع
91	صُورَة ناجحه
92	صُورَة نافِع
93	صُورَة هائِل
94	صُورَة وُدِّيّ
95	صُورَة يَسِير
96	صُورَة ٱسْتِباقِيّ
97	صُورَة ٱسْتِثْنائِيّ
98	صِفَة مُمَيَّز
99	طَرِيقَة إِبْداع

No.	Two Words Dimensional
100	طَرِيقَة إِيجابِيّ
101	طَرِيقَة استثائيه
102	طَرِيقَة بارِع
103	طَرِيقَة بَنّاء
104	طَرِيقَة جَمِيل
105	طَرِيقَة جَيِّد
106	طَرِيقَة حَضْرِيّ
107	طَرِيقَة حَماسِيّ
108	طَرِيقَة رائِع
109	طَرِيقَة سارّ
110	طَرِيقَة سَعِيد
111	طَرِيقَة سَلِس
112	طَرِيقَة سَهْل
113	طَرِيقَة شَغُوف
114	طَرِيقَة فَرِيد
115	طَرِيقَة فَعّال
116	طَرِيقَة كافِي
117	طَرِيقَة لافِت
118	طَرِيقَة ماهِر
119	طَرِيقَة مبهره
120	طَرِيقَة مُبْدِع
121	طَرِيقَة مُتَمَكِّن
122	طَرِيقَة مُتَمَيِّز
123	طَرِيقَة مُتْقَن
124	طَرِيقَة مُجْتَهِد
125	طَرِيقَة مُدْهِش
126	طَرِيقَة مُذْهِل
127	طَرِيقَة مُرِيح
128	طَرِيقَة مُرْبِح
129	طَرِيقَة مُرْضِي
130	طَرِيقَة مُسْتَمِرّ
131	طَرِيقَة مُفِيد
132	طَرِيقَة مُقْتَدِر
133	طَرِيقَة مُلائِم
134	طَرِيقَة مُلْفِت
135	طَرِيقَة مُمَيَّز
136	طَرِيقَة مُمْتِع
137	طَرِيقَة ناجِح
138	طَرِيقَة نافِع
139	طَرِيقَة هائِل
140	طَرِيقَة وُدِّيّ
141	طَرِيقَة يَسِير
142	طَرِيقَة اِسْتِباقِيّ
143	عَلَى رَغْم
144	غَنِيّ مَعْلُومَة
145	غَيْر مَسْبُوق
146	قَدْر كَبِير
147	كُلّ سُرُور
148	لا ضاهَى
149	مَشْهُود لِ
150	مُثِير إِعْجاب
151	مُنْقَطِع نَظِير

No.	Two Words Dimensional
152	نَحْو إِبْداع
153	نَحْو إيجابِيّ
154	نَحْو بَنّاء
155	نَحْو جَمِيل
156	نَحْو جَيِّد
157	نَحْو حَصْرِيّ
158	نَحْو حَماس
159	نَحْو رائِع
160	نَحْو سارّ
161	نَحْو سَعِيد
162	نَحْو سَلِس
163	نَحْو سَهْل
164	نَحْو شَغُوف
165	نَحْو فَرِيد
166	نَحْو فَعّال
167	نَحْو كافِي
168	نَحْو كَبِير
169	نَحْو لافِت
170	نَحْو ماهِر
171	نَحْو مبهر
172	نَحْو مَجْد
173	نَحْو مُبْدِع
174	نَحْو مُتَمَيِّز
175	نَحْو مُتَّقِن
176	نَحْو مُدْهِش
177	نَحْو مُذْهِل
178	نَحْو مُرِيح
179	نَحْو مُرْبِح
180	نَحْو مُرْضِي
181	نَحْو مُسْتَمِرّ
182	نَحْو مُفِيد
183	نَحْو مُفْرِح
184	نَحْو مُقْتَدِر
185	نَحْو مُلائِم
186	نَحْو مُلْفِت
187	نَحْو مُمَيَّز
188	نَحْو مُمْتِع
189	نَحْو ناجِح
190	نَحْو نافِع
191	نَحْو هائِل
192	نَحْو وُدِّيّ
193	نَحْو يَسِير
194	نَحْو اِسْتِباق
195	نَحْو اِسْتِثْنائِيّ
196	اِكْتِشاف مُهِمّ
197	اِكْتِشاف هامّ

Table A1. (a-3.iii) Positive Arabic Three Words Dimensional (*N*=13)

No.	Three Words Dimensional
1	إِلَى حَدّ كَبِير
2	شَكْل مُثِير إِعْجاب
3	صُورَة مُثِير إِعْجاب
4	طَرِيقَة مُثِير إِعْجاب
5	عَلَى شَكْل مُفِيد
6	عَلَى طَرِيقَة مُفِيد
7	عَلَى نَحْو رائِع
8	عَلَى نَحْو مُفِيد
9	فَرِيد مِن نَوْع
10	لا مَثِيل لِ
11	لا نَظِير لِ
12	لَيِس لِ مَثِيل
13	نَحْو مُثِير إِعْجاب

Table A2. (b-1) Negative English to Original Arabic Translation (*N =5,773*)

No.	English Word	Arabic Translation
1	abandon	يترك، يهجر، يتخلى، يتنازل
2	abandoned	متروك، ترك، تنازل، مهجور، مهمل، هجر، تخلى
3	abandoning	التخلي، يتخلى، التنازُل، يتنازل، الهجر، يهجر
4	abandonment	الترك، التخلي، الإعراض، الهجر
5	abdicated	تنازل، تخلى، تنحى، متروك، أعتزل
6	abdicates	يعتزل، يتنحى، يتنازل، يتخلى
7	abdicating	يعتزل، يتنحى، يتنازل، يتخلى، التنازل، التخلي، الأعتزال
8	abdication	التنازل، التخلي، الأعتزال
9	aberrant	شاذ، غير طبيعي، مضطرب، منحرف
10	aberration	الانحراف، الشذوذ، الأضطراب
11	aberrational	غير اعتيادي، غير طبيعي، مضطرب، شاذ
12	abetting	التحريض، يُحرِّض
13	abnormal	غير طبيعي، غير عادي، شاذ
14	abnormality	اختلال، اضطراب
15	abnormally	بشكل شاذ، بصورة شاذة، بنحو شاذ، بطريقة شاذة، بشكل غير طبيعي، بصورة غير طبيعية، بنحو غير طبيعي، بطريقة غير طبيعية
16	abolish	يلغي، يُزيل، يُبطل، يمحو، إلغاء، إبطال، إزالة
17	abolished	الغي، أزيل، أبطل، محا، ملغي
18	abolishes	يلغي، يزيل، يُبطل، يمحو
19	abolishing	يلغي، يزيل، يُبطل، يمحو، إلغاء، إبطال، إزالة
20	abrogate	يلغي، يفسخ، يُبطل، ينقض
21	abrogated	ألغى، فسخ، أبطل، نقض، ملغى، مُبطَل
22	abrogates	يلغي، يفسخ، يُبطل، ينقض، يسقط
23	abrogating	يلغي، يفسخ، يُبطل، ينقض، يسقط
24	abrogation	الإلغاء، إبطال، النقض
25	abrupt	مفاجئ، حاد، مباغت، فظ
26	abruptly	بصورة مفاجئة، بشكل مفاجئ، بنحو مفاجئ، بطريقة مفاجئة، بصورة مباغتة، بشكل مباغت، بنحو مباغت، بطريقة مباغتة، بصورة حادة، بشكل حاد، بنحو حاد، بطريقة حادة
27	abruptness	حدة
28	absence	فقدان، انعدام، الغياب، افتقار
29	absenteeism	التغيب
30	abuse	يسئ، ينتهك، يعتدي، اساءة، انتهاك، تعدي
31	abused	أساء، أنتهك، أعتدى
32	abusing	يسيء، ينتهك، يعتدي، اساءة، انتهاك، تعدي
33	abusive	تعسفي، مؤذي
34	abusively	بشكل تعسفي، بنحو تعسفي، بشكل مسيء، بنحو مسيء، بصورة مسيئة، بطريقة مسيئة
35	abusiveness	سوء المعاملة، الإساءة
36	accident	حادث، واقعة
37	accidental	غير مقصود، غير متعمد
38	accidentally	بطريق الخطأ، دون قصد، غير متعمد، سهو
39	accusation	الاتهام، التهمة، ادعاء
40	accuse	يلوم، يتهم، يدعي
41	accused	اتهم، متهم، ملام
42	accuses	يلوم، يتهم، يشكك، يدعي
43	accusing	يلوم، يتهم، يشكك، يدعي، لوم، ادعاء
44	acquiesce	الإذعان، الرضوخ، يُذعن، يرضخ
45	acquiesced	رضخ، أذعن
46	acquiesces	يُذعن، يرضخ
47	acquiescing	الإذعان، الرضوخ
48	acquit	يعفي، يبرئ

No.	English Word	Arabic Translation
49	acquits	يعفي، يبرئ
50	acquittal	مخالصة، تبرئة، براءة، إبراء
51	acquitted	أبرأ، تمت تبرئته، صدرت براءته
52	acquitting	إصدار براءة، إعلان براءة، تبرئة، إزالة التهم، يعفي، يبرئ
53	adulterate	يغش، يزيف، مزيف، مغشوش
54	adulterated	غش، زيف، مزيف، مغشوش
55	adulterating	يغش، يزيف، التزييف، الغش
56	adulteration	الغش، التزييف
57	adversarial	معارض، مناوئ، مناهض، عدائي، الخصومة
58	adversary	مناوئ، مناهض، عدو، منافس
59	adverse	ضارة، مناوئ، مناهض، سلبي، معاكس، مضاد، عاجز
60	adversely	بشكل سلبي، بصورة سلبية، بنحو سلبي، بطريقة سلبية، بشكل ضار، بنحو ضار، بصورة ضارة، بطريقة ضارة، بشكل معاكس، بنحو معاكس، بصورة معاكسة، بطريقة معاكسة
61	adversity	مصيبة، أزمة، شدة، محنة، نكسة
62	aftermath	عواقب
63	against	ضد، عكس
64	aggravate	يُثير، يصعب، يؤزم
65	aggravated	يُثير، يصعب، يؤزم، جسيم، متفاقم
66	aggravates	يُثير، يصعب، يؤزم
67	aggravating	يُثير، يصعب، يؤزم، جسيم، متفاقم
68	aggravation	إثارة، صعوبة، محذر
69	alerted	نبه، أنذِر، متأهِب، حذّر
70	alerting	إنذار، تحذير، ينبه، تنبيه، استنفار، تم إخطاره
71	alienate	يُبعد، ينفر، يعزل، ينبذ، ينقل ملكية
72	alienated	يُبعد، ينفر، يعزل، ينبذ، ينقل ملكية، منبوذ، مستبعد، معزول
73	alienates	يُبعد، ينفر، يعزل، ينبذ، ينقل ملكية
74	alienating	يُبعد، ينفر، يعزل، ينبذ، منبوذ، مستبعد، معزول
75	alienation	العزلة، إبعاد، نقل الملكية، النفور
76	allegation	اتهامات، المزاعم، الأفتراء
77	allege	يزعم، يحتج، يتذرع، يتهم، يدعي
78	alleged	يزعم، يحتج، يتذرع، يتهم، يدعي، مزعوم، ادعاءات، المدعاة
79	allegedly	يزعم انه، كما يزعم، حسب الادعاء
80	alleges	يزعم، يحتج، يتذرع، يتهم، يدعي
81	alleging	يزعم، يحتج، يتذرع، يتهم، يدعي، مزعوم، ادعاءات، المدعاة
82	annoy	يضايق، يزعج، ينزعج، يُغضب، يستفز
83	annoyance	الانزعاج، الازعاج، استياء، مضايقة
84	annoyed	ضايق، أزعج، أنزعج، آذى، متضايق، مزعَج، منزعج، غاضب
85	annoying	،يضايق، يزعج، ينزعج، متضايق، مزعَج، منزعج، غاضب، انزعاج، إزعاج، تضايق مضايقة
86	annoys	يضايق، يزعج، ينزعج، يُغضب، يستفز، يؤذي
87	annul	يُلغي، يُبطل، يفسخ
88	annulled	يُلغي، يُبطل، يفسخ، ملغي، مبطَل، موقوف
89	annulling	يُلغي، يُبطل، يفسخ، إبطال
90	annulment	الإلغاء، الإبطال، التعطيل
91	annuls	يُلغي، يُبطل، يفسخ
92	anomalous	شاذة، غير عادي، غريب، منحرف، غير طبيعي
93	anomalously	،بشكل غير طبيعي، بصورة غير طبيعية، بشكل غير طبيعي، بنحو غير طبيعي، بنحو شاذ بشكل شاذ، بصورة شاذة، بطريقة شاذة
94	anomaly	شذوذ، انحراف، اختلال
95	anticompetitive	مخالف لروح المنافسة، مناهض للتنافس، مضاد للمنافسة، ضد المنافسة، ضد المنافسة
96	antitrust	ضد الاحتكار، محاربة الاحتكار، مناهض للاحتكار، مضاد للاحتكار، مكافحة الاحتكار
97	argue	يحتج، يتجادل، يجادل، يدافع، يبرر

No.	English Word	Arabic Translation
98	argued	يحتج، يتجادل، يجادل، يدافع، يبرر
99	arguing	يحتج، يتجادل، يجادل، يدافع، يبرر، الجدال
100	argument	النزاع، الجدال، الخلاف، الحجة
101	argumentative	خلافي، جدلي، محل خلاف، محل جدل، محل نزاع
102	arrearage	متأخرة، تخلف عن السداد، تأخر عن السداد
103	arrearages	متأخرات، تخلف عن السداد، تأخر عن السداد
104	arrears	مستحقات غير مدفوعة، أقساط متأخرة، متأخرات، تأخير في الدفع، ديون معلقة
105	arrest	يعتقل، الاعتقال، يحتجز
106	arrested	اعتقل، محتجز، محبوس
107	artificially	بنحو مصطنع، بصورة اصطناعية، بشكل مصطنع
108	assault	يتعدى، يتهجم، يهاجم، التعدي، تهجُّم، الأعتداء
109	assaulted	اعتدى، هجم، هاجم، معتدى عليه، تعرض لاعتداء، تم الهجوم عليه
110	assaulting	يتعدى، يتهجم، يهاجم، التعدي، تهجُّم، الأعتداء
111	assertions	ادِّعاءات
112	attrition	استنزاف، تناقص، تآكل، انكماش
113	aversely	بطريقة عكسية، بشكل عكسي، بنحو عكسي، بصورة عكسية، بشكل سلبي، بنحو سلبي، بصورة سلبية، بطريقة سلبية
114	backdating	تاريخ رجعي، تأريخ مسبق
115	bad	سيء، رديء، السوء، غير صالح
116	bail	يكفل، انقاذ، الكفالة، الافراج
117	bailout	الإنقاذ، إغاثة مالية، دعم مالي طارئ، إسعاف
118	balk	يصد، يعيق، يتردد، عائق
119	balked	يصد، يعيق، يتردد، يتحفظ
120	bans	يحظر، يمنع
121	bankrupt	يفلس، مفلس، إفلاس، معسر، مديون
122	bankruptcy	إفلاس، إعسار
123	bankrupted	أفلس، مفلس، معسر، مديون
124	bankrupting	يفلس، مفلِس، إفلاس، إعسار، معسر
125	barred	يحظر، يمنع، يحجب، محجوب، محظور، ممنوع، مسدود، موقوف
126	barrier	السد، العائق، الحواجز
127	bottleneck	يعيق، مأزق، عائق، خانق
128	boycott	يقاطع، المقاطعة
129	boycotted	تم حظره، تمت مقاطعته، يقاطع
130	boycotting	يقاطع، المقاطعة
131	breach	يخرق، ينقض، ينتهك، خرق، مخالفة، ثغرة، إخلال، صدع، انتهاك، اختراق، فجوة
132	breached	يخرق، ينقض، ينتهك، مخترق، منتهك
133	breaching	يخرق، ينقض، ينتهك، مخترق، منتهك
134	break	يقتحم، ينتهك، يكسر، يخرق، ينهار
135	breakages	تلف، كسر، عجز
136	breakdown	انهيار، انقطاع، عطل، فشل، تعطل
137	bribe	يرشو، الرشوة
138	bribed	يرشو، الرشوة
139	bribery	الرشوة
140	bribing	يرشو، رشوة
141	burden	يثقل، يرهق، حمل، عبء
142	burdened	يثقل، يرهق، مثقل، محمل
143	burdening	يثقل، يرهق، مثقل، مرهق، الحمل، عبء
144	burdensome	مرهقة، ثقيل، قاسي
145	burned	يحرق، إحراق
146	calamitous	مدمر، كارثي، فاجع، مأساوي
147	calamity	مصيبة، أزمة، كارثة، فاجعة، محنة
148	cancel	يحذف، يلغي، يشطب

No.	English Word	Arabic Translation
149	canceled	يحذف، يلغي، مشطوب، مُلغى، مبطل، تم إلغاؤه
150	canceling	يحذف، يلغي، يشطب، مشطوب، مُلغى، مبطل
151	cancellation	الإلغاء، الشطب
152	cancelled	يحذف، يلغي، مشطوب، مُلغى، مبطل، تم إلغاؤه
153	cancelling	يحذف، يلغي، يشطب، مشطوب، مُلغى، مبطل
154	careless	مهمل، متساهل، مستهتر، متهور، طائش، غير مبالي
155	carelessly	بشكل متهور، بصورة متهورة، بطريقة متهورة، بنحو متهور، بشكل غير مبالي، بنحو غير مبالي
156	carelessness	اللامبالاة، الإهمال، التهور
157	catastrophe	مصيبة، أزمة، فاجعة، كارثة، محنة
158	catastrophic	مأساوي، مدمر، فاجع، كارثي، وخيمة
159	catastrophically	بنحو مأساوي، بشكل كارثي، بنحو كارثي، بشكل مأساوي
160	caution	الحيطة، الأحتراس، التروي، الحذر
161	cautionary	وقائي، تحذيري، احترازي
162	cautioned	أنذر، نبه، حذر
163	cautioning	ينذر، ينبه، يحذر، احتراس، تحذير، إنذار
164	cease	يوقف، يقطع، ينهي، التوقف، امتناع
165	ceased	يتوقف، يقطع، ينهي، موقف
166	ceasing	التوقف، إنهاء، إيقاف، امتناع
167	censure	يوبخ، يستهجن، ينتقد، يلوم، يستنكر، استنكار، انتقاد، توبيخ، استهجان، لوم
168	censured	يوبخ، يستهجن، ينتقد، يلوم، يستنكر
169	censuring	يوبخ، يستهجن، ينتقد، يلوم، يستنكر، استنكار، انتقاد، توبيخ، استهجان، لوم
170	challenge	يتحدى، يعترض، تحدي
171	challenged	يتحدى، يعترض، تحدي
172	challenging	التحدي، معقد، صعب
173	chargeoffs	ديون معدومة، خصم الديون، شطب مبالغ مدينة
174	circumvent	يتفادى، يتجنب، يراوغ، يتهرب
175	circumvented	يتفادى، يتجنب، يراوغ
176	circumventing	يتفادى، يتجنب، يراوغ، مراوغة، التحايل، الالتفاف
177	circumvention	التحايل
178	circumvents	يتفادى، يتجنب، يراوغ، يتهرب
179	claims	يطالب، يدعي، مطالبات، ادّعاءات
180	claiming	يطالب، يدعي، مطالبة، ادعاء
181	clawback	إسترداد أموال، استرداد مدفوعات، استرجاع مبالغ، استعادة أموال
182	closeout	تصفية، إغلاق
183	closings	ينهي، يقفل، يغلق، يصفي، تصفية، إغلاق، الاقفال
184	closure	إغلاق، اقفال، إنهاء
185	coerce	يجبر، يُكره، يرغم، يضطر
186	coerced	يجبر، يُكره، يرغم، يضطر، مجبر
187	coerces	يجبر، يُكره، يرغم
188	coercing	يجبر، يُكره، يرغم، الإجبار، الإكراه
189	coercion	الإجبار، الإكراه، القسر
190	coercive	قهري، إكراهي، إجباري، قسري، قمعي
191	collapse	يخفق، ينهار، يتهاوى، يسقط، انهيار، سقوط، تهاوي
192	collapsed	يخفق، ينهار، يتهاوى، يسقط، منهار
193	collapsing	يخفق، ينهار، يتهاوى، يسقط، الانهيار، إخفاق، منهار
194	collision	تضارب، تصادم، اصطدام
195	collude	يتواطأ، يتآمر
196	colluded	يتواطأ، يتآمر
197	colludes	يتواطأ، يتآمر
198	colluding	يتواطأ، يتآمر، متواطئ، التواطؤ، التآمر
199	collusion	التواطؤ، التآمر، مؤامرة

No.	English Word	Arabic Translation
200	collusive	متواطئ، متآمر
201	complain	يتذمر، يشكو، ينتقد، يشتكي، شكوى، التذمر
202	complained	يتذمر، يشكو، ينتقد، يشتكي
203	complaining	يتذمر، يشكو، ينتقد، يشتكي، شكوى، التذمر
204	complains	يتذمر، يشكو، ينتقد، يشتكي
205	complaint	تذمر، شكوى، لوم، اعتراض
206	complicate	يصعب
207	complicated	يصعب، معقد
208	complicates	يصعب
209	complicating	يصعب، التعقيد
210	complication	التعقيد، الصعوبة، إشكالية
211	compulsion	إلحاح، إجبار، إلزام، إكراه، قسر
212	concealed	يكتم، يخفي، يحجب، مخفي، مخبأة، سري
213	concealing	يكتم، يخفي، يحجب، مخفي، مخبأة، سري
214	concede	يتنازل، يسلم، يقبل، يعترف، يرضخ، يذعن
215	conceded	يتنازل، يسلم، يقبل، يعترف، يرضخ، يذعن
216	concedes	يتنازل، يسلم، يقبل، يعترف، يرضخ، يذعن
217	conceding	يتنازل، يسلم، يقبل، يعترف، يرضخ، يذعن، التنازل، الاستسلام، الإذعان
218	concern	يقلق، القلق، الاكتراث
219	concerned	يقلق، مقلق
220	conciliating	يصالح، المصالحة، التسوية، التهدئة، الاسترضاء
221	conciliation	المصالحة، التسوية، التهدئة، الاسترضاء
222	condemn	يشجب، يستهجن، يدين، يستنكر، يشجب، يوبخ، يجرم، يندد
223	condemnation	الشجب، الاستهجان، التنديد، التوبيخ، التجريم
224	condemned	يشجب، يستهجن، يدين، يستنكر، يشجب، يوبخ، يجرم، يندد، مُدان
225	condemning	يشجب، يستهجن، يدين، يستنكر، يشجب، يوبخ، يجرم، يندد، مُدان، الشجب، الاستهجان، التنديد، التوبيخ، التجريم
226	condemns	يشجب، يستهجن، يدين، يستنكر، يشجب، يوبخ، يجرم، يندد
227	condone	يتنازل، يتغاضى، يغفر
228	condoned	يتنازل، يتغاضى، يغفر
229	confess	يعترف
230	confessed	يعترف، معترف
231	confesses	يعترف
232	confessing	يعترف، الاعتراف
233	confession	الاعتراف
234	confined	يقيد، يحتجز، يحبس، يعزل، محصور، مقيد، محتجز، معزول
235	confinement	الحجز
236	confines	يحصر، يقيد، يحتجز، يحبس
237	confining	يحصر، يقيد، يحتجز، يحبس، محصور، مقيد، محتجز، معزول
238	confiscate	ينتزع، يصادر، يستولي، يحجز
239	confiscated	ينتزع، يصادر، يستولي، يحجز، مصادر
240	confiscates	ينتزع، يصادر، يستولي، يحجز
241	confiscating	ينتزع، يصادر، يستولي، يحجز
242	confiscation	الانتزاع، المصادرة، الأحتجاز، نزع ملكية
243	conflict	يتضارب، يتناقض، يتعارض، الخلاف، النزاع، الصراع، التعارض، التضارب
244	conflicted	يتضارب، يتناقض، يتعارض، متضارب، متناقض، متعارض
245	conflicting	يتضارب، يتناقض، يتعارض، متضارب، متناقض، متعارض، الخلاف، النزاع، الصراع، التعارض، التضارب
246	confront	يجابه، يتصدى
247	confrontation	المواجهة، المجابهة، النزاع
248	confrontational	عدائي، استفزازي، تصادمي، جدالي
249	confronted	يجابه، يتصدى

No.	English Word	Arabic Translation
250	confronting	يجابه، يتصدى، المواجهة، المجابهة، النزاع
251	confronts	يجابه، يتصدى
252	confuse	يضلل، يربك، يشوش، يخلط
253	confused	يضلل، يربك، يشوش، مشوش
254	confuses	يضلل، يربك، يشوش
255	confusing	مُحيّر، مربك، يربك، ملتبس، إرباك، مشوش، يشوش، التشويش
256	confusingly	،بطريقة مربكة، بصورة مربكة، بشكل مربك، بنحو مربك، بشكل محير، بصورة محيرة بطريقة محيرة، بنحو محير
257	confusion	ارتباك، إرباك، تداخل
258	conspiracy	المؤامرة، المكيدة، التآمر
259	conspirator	متآمر، متواطئ
260	conspiratorial	تآمري، تواطُئيّ
261	conspire	يتآمر، يكيد، يتواطأ
262	conspired	يتآمر، يكيد، يتواطأ، متآمر، متواطئ
263	conspires	يتآمر، يكيد، يتواطأ
264	conspiring	يتآمر، يكيد، يتواطأ، متآمر، متواطئ، المؤامرة، المكيدة، التآمر
265	contempt	الازدراء، السخرية، الاستخفاف، الاحتقار
266	contend	يجادل، يكافح، يناضل، ينافس
267	contended	يجادل، يكافح، يناضل، ينافس
268	contending	يجادل، يكافح، يناضل، ينافس
269	contends	يجادل، يكافح، يناضل، ينافس
270	contention	الجدال، الخلاف، التنازع، الصراع، النزاع
271	contentious	مثير للجدل، موضع خلاف، خلافي، شائك، متنازع عليه، مثير للنزاع
272	contentiously	بشكل مثير للجدل، بنحو مثير للجدل، بصورة مثيرة للجدل، بطريقة مثيرة للجدل، بشكل جدلي، بصورة جدلية، بنحو جدلي، بطريقة جدلية
273	contested	يصارع، ينازع، موضع خلاف، متنافس عليه، متنازع عليه، مختلف عليه، محل نزاع
274	contesting	يصارع، ينازع، الصراع، النزاع
275	contraction	الانقباض، التقلص، التراجع، التضاؤل، الانكماش
276	contradict	يتناقض، يناقض، يتعارض، يعارض، يتضارب
277	contradicted	يتناقض، يناقض، يتعارض، يعارض، يتضارب، مناقض، متعارض، متناقض
278	contradicting	،يتناقض، يناقض، يتعارض، يعارض، يتضارب، مناقض، متعارض، متناقض، التناقض التعارض، التضارب
279	contradiction	التناقض، التعارض، التضارب
280	contradictory	متعارض، متناقض، مناقضة، متباين
281	contradicts	يتناقض، يناقض، يتعارض، يعارض، يتضارب
282	contrary	معاكس، معارض، مخالف، مناقض، متناقض، مضاد
283	controversial	مثير للجدل، موضع خلاف، مثير للخلاف، متنازع عليه
284	controversy	النزاع، الخلاف، الجدل، الجدال
285	convict	يُجرّم، يُدين، مجرم، مدان
286	convicted	يُجرّم، يُدين، مجرم، مدان
287	convicting	يُجرّم، يُدين، التجريم، مجرم، مدان
288	conviction	التجريم، الإدانة
289	corrected	يصحح، يعدل، مصحح
290	correcting	يصحح، يعدل، مصحح، التصحيح، التعديل
291	correction	التصحيح، التعديل
292	corrects	يصحح، يعدل
293	corrupt	يفسد، الفساد، فاسد
294	corrupted	يفسد، فاسد
295	corrupting	يفسد، الفساد، فاسد
296	corruption	الفساد
297	corruptly	بشكل فاسد، بنحو فاسد، بصورة فاسدة، بطريقة فاسدة
298	corruptness	الفساد

No.	English Word	Arabic Translation
299	costly	مكلف، غالي، باهظ
300	counterclaim	ادعاء مضاد، مطالبة مضادة، دعوى مضادة
301	counterclaimed	ادعاء مضاد، مطالبة مضادة، دعوى مضادة
302	counterclaiming	ادعاء مضاد، مطالبة مضادة، دعوى مضادة
303	counterfeit	يزور، يزيف، التزوير، التزييف، مزورة، مزيف
304	counterfeited	يزور، يزيف، مزورة، مزيف
305	counterfeiter	مزيف، مزور
306	counterfeiting	يزور، يزيف، التزوير، التزييف، مزورة، مزيف
307	countermeasure	الإجراء المضاد، تدابير مواجهة، إجراء مضاد، تدبير مضادة، استراتيجية مضادة، تدبير مضاد، وسيلة مضادة
308	crime	الجريمة، الجناية
309	criminal	مجرم، إجرامي، جنائي
310	criminally	بصورة إجرامية، بنحو إجرامي، بشكل إجرامي
311	crisis	أزمة، مصيبة
312	critically	بشكل حرج، بنحو حرج، بصورة حرجة، بطريقة حرجة
313	criticism	الاستنكار، الإنتقاد، التوبيخ
314	criticize	ينتقد
315	criticized	ينتقد
316	criticizes	ينتقد
317	criticizing	ينتقد، الإنتقاد
318	crucial	عصيب، محوري، مصيري، ضروري، حرج
319	crucially	بشكل ضروري، بنحو ضروري، بصورة ضرورية
320	culpability	الذنب، الإثم، اللّوم
321	culpable	مذنب، ملام، مؤاخذ
322	culpably	بصورة مذنبة، بشكل مذنب، بنحو مذنب
323	cumbersome	شاق، مرهق، معقد
324	curtail	يقلص
325	curtailed	يقلص، مقلص
326	curtailing	يقلص، التقليص، مقلص
327	curtailment	التقليص
328	curtails	يقلص
329	cut	يخفض، يقطع، يوقف
330	cutback	التقشف، التقليص، الخفض
331	cyberattack	هجوم معلوماتي
332	cyberattacks	هجوم إلكتروني، هجمات معلوماتية
333	cyberbullying	التنمر الإلكتروني، التنمر عبر الانترنت، التنمر إلكتروني، المضايقة الإلكترونية
334	cybercrime	الجريمة الإلكترونية، الجريمة الرقمية
335	cybercriminal	قرصان إلكتروني، مجرم إلكتروني، مخترق إلكتروني
336	cybercriminals	قرصان إلكتروني، مجرم إلكتروني، مخترق إلكتروني
337	damage	يتلف، يضر، الضرر، التلف
338	damaged	يتلف، يضر، متضررة، تالف
339	damaging	يتلف، يضر، متضررة، تالف، الضرر، التلف
340	dampen	يكبح، يثبط، يخمد
341	dampened	كبح، يثبط، يخمد
342	danger	الخطر، التهديد، الخطورة
343	dangerous	خطير
344	dangerously	بصورة خطيرة، بشكل خطير، بنحو خطير، بطريقة خطره
345	deadlock	الجمود، مأزق، طريق مسدود
346	deadlocked	عالق، مأزق
347	deadlocking	الجمود، مأزق، عالق
348	deadweight	عبء
349	deadweights	أعباء غير مجدية، العبء

No.	English Word	Arabic Translation
350	debarment	الحرمان، التجريد
351	debarred	محظور، ممنوع، محروم
352	deceased	المتوفى، الميت
353	deceit	الخداع، التضليل، الأحتيال
354	deceitful	مخادع، مضلل، محتال
355	deceitfulness	الخداع، التضليل، الأحتيال
356	deceive	يضلل، يغش، يخدع
357	deceived	يضلل، يغش، يخدع، مضلل، مخادع
358	deceives	يضلل، يغش، يخدع
359	deceiving	يضلل، يغش، يخدع، الخداع، التضليل، الأحتيال، مضلل، مخادع، محتال
360	deception	الخداع، التضليل، الأحتيال
361	deceptive	مضلل، مخادع، محتال
362	deceptively	بشكل مخادع، بنحو مخادع، بصورة مخادعة، بطريقة مخادعة، بشكل مضلل، بنحو مضلل، بصورة مضللة، بطريقة مضللة
363	decline	،ينخفض، يهبط، ينحدر، يتدنى، يتدهور، التراجع، التدهور، الهبوط، الانكماش، الأنحدار الانخفاض، التدني
364	declined	ينخفض، يهبط، ينحدر، يتدنى، يتدهور، هابط، منخفض، متراجع، متدني
365	declining	،ينخفض، يهبط، ينحدر، يتدنى، يتدهور، هابط، منخفض، متراجع، متدني، التراجع التدهور، الهبوط، الانكماش، الأنحدار، التدني
366	deface	يشوه، يعبث، يتلف، يطمس
367	defaced	يشوه، يعبث، يتلف، يطمس، مشوه
368	defacement	التشويه، العبث
369	defamation	التشهير، الإساءة، الافتراء، القذف
370	defamatory	افترائيّ، تشهيري
371	defame	يشهر، يسيء، يفتري، يقذف
372	defamed	مشوه
373	defames	يشهر، يسيء، يفتري، يقذف
374	defaming	يشهر، يسيء، يفتري، يقذف، مشوه، التشهير، الإساءة، الافتراء، القذف
375	default	يتخلف، يهمل، يعجز، التخلف، الأهمال، الفشل، التقصير، الإخفاق، العجز
376	defaulted	يتخلف، يهمل، يعجز، متخلف، متعثر، عاجز
377	defaulting	،يتخلف، يهمل، يعجز، متخلف، متعثر، عاجز، التخلف، الأهمال، الفشل، التقصير الإخفاق، العجز
378	defeat	ينهزم، يفشل، الهزيمة، الفشل
379	defeated	ينهزم، يفشل، فاشل
380	defeating	ينهزم، يفشل، فاشل، الهزيمة، الفشل
381	defect	عيب، خلل
382	defective	متضرر، تالف
383	defend	يدافع
384	defendant	المتهم، المدعى عليه
385	defended	يدافع
386	defending	يدافع
387	defends	يدافع
388	defensive	دفاعي، وقائي
389	defer	يؤجل، يرجئ، يحيل
390	deficiency	قصور، نقص، عجز، خلل
391	deficient	ناقص، ضعيف، عاجز
392	deficit	العجز، النقص
393	defraud	يحتال، يخدع، يضلل، الاحتيال، التضليل
394	defrauded	يحتال، يخدع، يضلل
395	defrauding	يحتال، يخدع، يضلل، الاحتيال، التضليل، مضلل
396	defrauds	يحتال، يخدع، يضلل
397	defunct	منحل، بائدة

No.	English Word	Arabic Translation
398	degradation	التراجع، التدهور
399	degrade	يتدهور، يخفض، ينخفض، يقلل
400	degraded	متدهورة، مترديـة، متدهور، متراجعة
401	degrades	يتدهور، يخفض، ينخفض، يقلل
402	degrading	يتدهور، يخفض، ينخفض، يقلل
403	delay	يؤجل، يرجئ، يؤخر، التأجيل، التأخير
404	delayed	يؤجل، يرجئ، يؤخر، مؤجل، متأخر، مؤخر
405	delaying	يؤجل، يرجئ، يؤخر، مؤجل، متأخر، مؤخر، التأجيل، التأخير
406	deleterious	ضار، مؤذي، مُضر
407	deliberate	متعمد
408	deliberated	متعمد
409	deliberately	بشكل متعمد، بنحو متعمد، بصورة متعمدة، بطريقة متعمدة
410	delinquency	التأخر، الأهمال، التقصير، الجنوح
411	delinquent	متعثر، متأخر، مهمل، مقصر، جانح
412	delinquently	بشكل متأخر، بنحو متأخر، بصورة متأخر، بطريقة متأخرة
413	delist	يشطب، يلغي إدراج
414	delisted	يشطب، يلغي إدراج، مشطوب
415	delisting	يشطب، يلغي إدراج، مشطوب
416	delists	يشطب، يلغي إدراج
417	demise	زوال
418	demised	زوال
419	demising	زوال
420	demolish	يهدم
421	demolished	يهدم
422	demolishes	يهدم
423	demolishing	يهدم، الهدم
424	demolition	الهدم
425	demote	يخفض، يقلل، ينحي
426	demoted	يخفض، يقلل
427	demotes	يخفض، يقلل، ينحي
428	demoting	يخفض، يقلل
429	demotion	إغلاق، تصفية
430	denial	إنكار، رفض
431	denied	ينكر، يرفض، مرفوض
432	denies	ينكر، يرفض
433	denigrate	يشوِّه سمعة
434	denigrated	يشوِّه سمعة
435	denigrates	يشوِّه سمعة
436	denigrating	يشوِّه سمعة، تشويه السمعة
437	denigration	تشويه السمعة
438	deny	ينكر، يرفض
439	denying	ينكر، يرفض، إنكار، الرفض
440	deplete	يستنزف، يستنفد
441	depleted	يستنزف، يستنفد
442	depletes	يستنزف، يستنفد
443	depleting	يستنزف، يستنفد، الاستنزاف
444	depletion	الاستنزاف، النضوب
445	deprecation	التقليل، انخفاض القيمة، استنكار
446	depress	يقلل، يضغط، يخفض، يثبط
447	depressed	يقلل، يضغط، يخفض، يثبط
448	depresses	يقلل، يضغط، يخفض، يثبط
449	depressing	يقلل، يضغط، يخفض، يثبط، محبطة

No.	English Word	Arabic Translation
450	deprivation	الفقدان، الحرمان، الافتقار
451	deprive	يجرد، يحرم
452	deprived	يجرد، يحرم، محروم
453	deprives	يجرد، يحرم
454	depriving	يجرد، يحرم، الحرمان، التجريد
455	derelict	مهجورة، المهملة، مهمل
456	dereliction	الأهمال، التقصير
457	derogatory	مهين، مسيء
458	destabilization	عدم الاستقرار، الزعزعة
459	destabilize	يزعزع استقرار، يخل بأستقرار
460	destabilized	يزعزع استقرار، يخل بأستقرار، مزعزع، مضطرب، غير مستقر
461	destabilizing	يزعزع استقرار، يخل بأستقرار، مزعزع، مضطرب، غير مستقر، عدم الاستقرار، الزعزعة
462	destroy	يدمر، يتلف، يخرب
463	destroyed	يدمر، يتلف، يخرب، مدمر، تالف
464	destroying	يدمر، يتلف، يخرب، مدمر، تالف، إتلاف، تخريب
465	destroys	يدمر، يتلف، يخرب
466	destruction	خراب، تدمير، دمار
467	destructive	هدَّام، مدمر
468	detain	يستوقف، يعتقل، يحتجز
469	detained	يستوقف، يعتقل، يحتجز، موقوف، معتقل، محتجز
470	detention	الاعتقال، الاحتجاز
471	deter	يمنع، يردع
472	deteriorate	يتدهور، يتردى
473	deteriorated	يتدهور، يتردى
474	deteriorates	يتدهور، يتردى
475	deteriorating	يتدهور، يتردى، متدهور، متردي، التدهور
476	deterioration	التدهور
477	deterred	يمنع، يردع، يثني
478	deterrence	الردع
479	deterrent	رادع
480	deterring	يمنع، يردع، يثني
481	deters	يمنع، يردع، يثني
482	detract	ينتقص، يقلل
483	detracted	ينتقص، يقلل
484	detracting	ينتقص، يقلل، الانتقاص
485	detriment	أذى، ضرر
486	detrimental	ضار، مؤذي
487	detrimentally	بطريقة ضارة، بصورة مضرة، بشكل ضار، بنحو ضار، بشكل مؤذي، بصورة مؤذية، بطريقة مؤذية، بنحو مؤذي
488	devalue	ينقص قيمة، يقلل قيمة، يخفض قيمة
489	devalued	ينقص قيمة، يقلل قيمة، يخفض قيمة، منخفض القيمة
490	devalues	ينقص قيمة، يقلل قيمة، يخفض قيمة
491	devaluing	ينقص قيمة، يقلل قيمة، يخفض قيمة، منخفض القيمة، تخفيض القيمة، تقليل القيمة
492	devastate	يدمر، يخرب
493	devastated	يدمر، يخرب، مدمر، محطم
494	devastating	يدمر، يخرب، مدمر، محطم، وخيمة
495	devastation	الدمار، الخراب
496	deviate	يحيد، يشذ، ينحرف
497	deviated	يحيد، يشذ، ينحرف، منحرف
498	deviating	يحيد، يشذ، ينحرف، منحرف، الانحراف، الشذوذ
499	deviation	الانحراف، الشذوذ

No.	English Word	Arabic Translation
500	devolve	ينحل، يؤول، ينحدر، يتدنى
501	devolved	ينحل، يؤول، ينحدر، يتدنى، متدهور، منحدر
502	devolves	ينحل، يؤول، ينحدر، يتدنى
503	devolving	ينحل، يؤول، ينحدر، يتدنى
504	difficult	شاق، صَعب
505	difficultly	،بشكل صعب، بنحو صعب، بصورة صعبة، بطريقة صعبة، بشكل شاق، بنحو شاق بصورة شاقة، بطريقة شاقة
506	difficulty	عائق، صعوبة
507	diminish	يقلل، يتضاءل
508	diminished	يتضاءل، يقلل، يخفض
509	diminishes	يتضاءل، يقلل، يخفض
510	diminishing	يتضاءل، يقلل، يخفض، التضاؤل
511	diminution	النقصان، التضاؤل
512	disadvantage	عيب، مساوئ، عائق
513	disadvantaged	محروم، متضرر، ناقص
514	disadvantageous	ضار، مضر، غير مفيد، عديم الفائدة، غير مؤات، غير ملائم
515	disaffiliation	انفصال، عدم الانتماء، قطع الصلة، فك الارتباط
516	disagree	يرفض، يتعارض، يعترض، يختلف، يناقض، لا يوافق، لا يتفق
517	disagreeable	مزعج، غير مقبول، غير مرغوب فيه، غير متفق علية
518	disagreed	يرفض، يتعارض، يعترض، يختلف، يناقض، لا يوافق، لا يتفق
519	disagreeing	يرفض، يتعارض، يعترض، يختلف، يناقض
520	disagreement	الخلاف، النزاع، التعارض
521	disagrees	يرفض، يتعارض، يعترض، يختلف، يناقض، لا يوافق، لا يتفق
522	disallow	يرفض، يمنع، يحظر، لا يقر، لا يسمح
523	disallowance	الرفض، المنع، عدم السماح، عدم الموافقة
524	disallowances	الرفض، المنع، عدم السماح، عدم الموافقة
525	disallowed	يرفض، يمنع، يحظر، مرفوض، محظور، مرفوض، ممنوع، غير مسموح به، غير مقبول، غير مسموح
526	disallowing	يرفض، يمنع، يحظر، مرفوض، محظور، مرفوض، ممنوع، غير مسموح به، غير مقبول، غير مسموح
527	disallows	يرفض، يمنع، يحظر، لا يقر، لا يسمح
528	disappear	يضمحل، يتوارى، يختفي، يتلاشى
529	disappearance	التلاشي، الاختفاء
530	disappeared	يختفي، يتلاشى، مختفي
531	disappearing	يختفي، يتلاشى، التلاشي، الاختفاء
532	disappears	يختفي، يتلاشى
533	disappoint	يحبط، يخيب، يخذل
534	disappointed	يحبط، يخيب، يخذل، محبط
535	disappointing	يحبط، يخيب، يخذل، محبط، الإحباط، الخذلان
536	disappointingly	بشكل محبط، بصورة محبطة، بنحو محبط، بطريقة محبطة، بشكل مؤسف، بصورة مؤسفة، بنحو مؤسف، بطريقة مؤسفة
537	disappointment	الإحباط، الخذلان، خيبة أمل
538	disappoints	يحبط، يخيب، يخذل
539	disapproval	الرفض، الاستنكار، عدم الموافقة، عدم الرضا
540	disapprove	يرفض، يستنكر، لا يوافق
541	disapproved	يرفض، يستنكر، مرفوض
542	disapproves	يرفض، يستنكر، لا يوافق
543	disapproving	يرفض، يستنكر، لا يوافق، الرفض، عدم الموافقة
544	disassociates	ينأى، يتبرأ، ينفصل
545	disassociating	ينأى، يتبرأ، ينفصل، قطع العلاقة
546	disassociation	التفكك، الأنفصال، قطع العلاقة
547	disaster	بلاء، كارثة، مصيبة، فاجعة

No.	English Word	Arabic Translation
548	disastrous	فاجع، فادح، مأساوي، كارثي
549	disastrously	بشكل فادح، بنحو فادح، بطريقة فادحة، بصورة فادحة
550	disavow	ينكر، يتنصل، يتبرأ
551	disavowal	إنكار، تنصُّل
552	disavowed	ينكر، يتنصل، يتبرأ
553	disavowing	ينكر، يتنصل، يتبرأ، الإنكار، التنصل
554	disavows	ينكر، يتنصل، يتبرأ
555	disciplinary	انضباطي، تأديبي
556	disclaim	يتنصل، يتبرأ، ينفي، يخلي مسؤولية
557	disclaimed	يتنصل، يتبرأ، ينفي، يخلي مسؤولية
558	disclaimer	إخلاء مسؤولية
559	disclaiming	يتنصل، يتبرأ، ينفي، يخلي مسؤولية، إخلاء مسؤولية
560	disclaims	يتنصل، يتبرأ، ينفي، يخلي مسؤولية
561	disclose	يفصح، يفشي
562	disclosed	يفصح، يفشي
563	discloses	يفصح، يفشي
564	disclosing	يفصح، يفشي، إفشاء
565	discontinuance	الأنقطاع، الأيقاف، التوقف
566	discontinuation	التخارج، الأيقاف، التوقف
567	discontinue	يوقف، يُنهي، ينقطع
568	discontinued	يوقف، يُنهي، ينقطع، موقوف، متوقف
569	discontinues	يوقف، يُنهي، ينقطع
570	discontinuing	يوقف، يُنهي، ينقطع، موقوف، متوقف، الأيقاف، الأنقطاع
571	discourage	يحبط، ينفر، يثني، يثبط، الأحباط
572	discouraged	يحبط، ينفر، يثني، يثبط، مُحبط، مثبط
573	discourages	يحبط، ينفر، يثني، يثبط
574	discouraging	يحبط، ينفر، يثني، يثبط، مُحبط، مثبط، الأحباط
575	discredit	يضعف سمعة، يشوه سمعة، يسيء سمعة، يفقد المصداقية، يجرد من الثقة
576	discredited	يضعف سمعة، يشوه سمعة، يسيء سمعة، يفقد المصداقية
577	discrediting	يضعف سمعة، يشوه سمعة، يسيء سمعة، يفقد المصداقية، فقدان الثقة
578	discrepancy	التفاوت، التباين، التضارب، الأختلاف، التناقض
579	disfavor	يعارض، لا يستحسن، استياء، عدم الاستحسان
580	disfavored	يعارض، لم يستحسن، غير مرغوب به، غير مفضل، غير مستحسن
581	disfavoring	يعارض، لا يستحسن، يتحيز ضد، غير مرغوب به، غير مفضل، غير مستحسن، استياء، عدم الاستحسان
582	disgorge	يعيد أرباح، يتخلى عن أرباح، يجبر على إعادة، يلزم بدفع
583	disgorged	يعيد أرباح، يتخلى عن أرباح، يجبر على إعادة، يلزم بدفع
584	disgorgement	الأرباح غير المشروعة، التعويضات
585	disgorges	يعيد أرباح، يتخلى عن أرباح، يجبر على إعادة، يلزم بدفع
586	disgorging	يعيد أرباح، يتخلى عن أرباح، يجبر على إعادة، يلزم بدفع، إعادة إجبارية
587	disgrace	خزي، عار، فضيحة
588	disgraceful	مهين، مشين، مخزي، مثير للاشمئزاز
589	disgracefully	بشكل مهين، بنحو مهين
590	dishonest	غير أمين، غير صادق
591	dishonestly	بشكل مخادع، بنحو مخادع
592	dishonesty	الكذب، الخداع، عدم الصدق، عدم الأمانة
593	dishonor	يخزي، يهين
594	dishonorable	مخزي، غير شريف، غير أخلاقي
595	dishonorably	بشكل مخزي، بنحو مخزي، بطريقة غير شريفة، بصورة غير شريفة
596	dishonored	مخزي، يهين، مهين
597	dishonoring	يخزي، يهين، مهين، إهانة
598	disincentives	مثبط، غير مشجع

No.	English Word	Arabic Translation
599	disinterested	غير مهتم، غير مبالٍ
600	disinterestedly	بشكل لا مبال، بشكل غير مبالي
601	disinterestedness	عدم الاهتمام
602	disloyal	خائن، غير أمين، غير مخلص
603	disloyally	بشكل غير مخلص، بنحو غير مخلص
604	disloyalty	الخيانة، عدم الإخلاص، عدم الولاء، عدم الوفاء
605	dismal	كئيب، محبط، سيء
606	dismally	بشكل سيء، بنحو سيء، بصورة سيئة، بشكل محبط، بنحو محبط، بصورة محبطة
607	dismiss	يطرد، يرفض
608	dismissal	الإقالة، التسريح، الطرد
609	dismissed	يطرد، يرفض، تم رفضه، مستبعد
610	dismisses	يطرد، يرفض
611	dismissing	يطرد، يرفض، الإقالة، التسريح، الطرد
612	disorderly	فوضوي، عشوائي، بشكل غير منظم
613	disparage	يحتقر، ينتقص، يستهزئ، التحقير، الانتقاص، الاستخفاف
614	disparaged	يحتقر، ينتقص، يستهزئ
615	disparagement	الازدراء، الاستخفاف، الاستهزاء
616	disparages	ينتقص، يسخر، يحتقر
617	disparaging	يحتقر، ينتقص، يستهزئ، التحقير، الانتقاص، الاستخفاف
618	disparagingly	بشكل ازدرائي، بنحو ازدرائي، بصورة ازدرائية، بطريقة ازدرائية
619	disparity	تباين، تغاير، تفاوت
620	displace	يزيح
621	displaced	مزاح، مستبدل
622	displacement	الإزاحة، الأستبدال، الإحلال
623	displaces	يزيح
624	displacing	يزيح، مستبدل
625	dispose	التخلص، يتخلص
626	dispossess	يصادر، ينزع، يجرد، ينتزع
627	dispossessed	يصادر، ينزع، يجرد، ينتزع، مصادر، منزوع
628	dispossesses	يصادر، ينزع، يجرد، ينتزع
629	dispossessing	يصادر، ينزع، يجرد، ينتزع، مصادر، منزوع
630	disproportion	التفاوت، الاختلال، عدم التوازن، عدم التناسب
631	disproportional	غير متساوي، غير متوازن، غير متكافئ، غير متناسب، غير متجانس
632	disproportionate	،غير متساوي، غير متناسبة، غير المتناسب، غير متوازن، غير متناسب، غير متكافئ غير متجانس
633	disproportionately	بشكل غير متناسب، بشكل غير متساوي، بشكل غير متوازن، بشكل غير متكافئ، بشكل غير متجانس
634	dispute	يجادل، ينازع، يعترض، الجدال، الاعتراض، الخلاف، النزاع
635	disputed	يجادل، ينازع، يعترض، محل جدال، متنازع عليه، محل خلاف
636	disputing	يجادل، ينازع، يعترض، الجدال، الاعتراض، الخلاف، النزاع
637	disqualification	إلغاء الأهلية، فقدان الأهلية، عدم الأهلية، تجريد من الأهلية
638	disqualified	فاقد الأهلية، غير مؤهل، ملغى أهليته، مستبعد، منسحب
639	disqualifies	يستبعد، يقرر عدم أهلية، يجرد من الأهلية، يفقد الأهلية
640	disqualify	يستبعد، يقرر عدم أهلية، يجرد من الأهلية، يفقد الأهلية، عدم أهلية، غير مؤهل
641	disqualifying	إلغاء الأهلية، فقدان الأهلية، عدم الأهلية، تجريد من الأهلية
642	disregard	يتغاضى، يتجاهل، يتغافل، يهمل، التجاهل، الاستخفاف، الإهمال
643	disregarded	يتغاضى، يتجاهل، يتغافل، يهمل، مهمل
644	disregarding	يتغاضى، يتجاهل، يتغافل، يهمل، مهمل، التجاهل، الاستخفاف، الإهمال
645	disreputable	سيء السمعة، ضار بالسمعة
646	disrepute	عار، سيء السمعة، سمعة سيئة
647	disrupt	يعرقل، يشوش، يربك
648	disrupted	يعرقل، يشوش، يربك، مربك

No.	English Word	Arabic Translation
649	disrupting	يعرقل، يشوش، يربك، مربك
650	disruption	العرقلة، الإرباك، الإخلال
651	disruptive	معرقل، مربك
652	disrupts	يعرقل، يشوش، يربك
653	dissatisfaction	استياء، سخط، تذمر، امتعاض، عدم الرضا
654	dissatisfied	ممتعض، غير راض، عدم الرضا، مستاء
655	dissent	يعارض، ينشق، المعارضة
656	dissented	يعارض، ينشق، منشق، معارض
657	dissenter	معارض، منشق
658	dissenting	يعارض، ينشق، منشق، معارض، المعارضة
659	dissident	معارض، منشق
660	dissolution	التصفية
661	distort	يشوه، يزيف، يُحرف
662	distorted	يشوه، يزيف، يُحرف، مشوه، مزيف، محرف، التشويه، التزييف، التحريف
663	distorting	يشوه، يزيف، يُحرف، مشوه، مزيف، محرف
664	distortion	التشويه، التزييف، التحريف
665	distorts	يشوه، يزيف، يُحرف
666	distract	يربك، يشتت
667	distracted	يربك، يشتت
668	distracting	يربك، يشتت
669	distraction	الإرباك
670	distracts	يربك، يشتت
671	distress	الضائقة، المحنة، الشدة
672	distressed	متعثرة
673	disturb	يشوش، يضطرب، يقلق، يعوق
674	disturbance	اضطراب
675	disturbed	مضطرب، غير مستقر، مقلق
676	disturbing	يشوش، يضطرب، يقلق، يعوق، مقلق
677	disturbs	يشوش، يضطرب، يقلق، يعوق
678	diversion	الإنحراف، التضليل، التشتيت
679	divert	يلهي، ينحرف، يبعد
680	diverted	يلهي، ينحرف، يبعد
681	diverting	يلهي، ينحرف، يبعد، منحرف
682	diverts	يلهي، ينحرف، يبعد
683	divest	يجرد، يتخلص، يتجرد
684	divested	يجرد، يتخلص، يتجرد
685	divesting	يجرد، يتخلص، يتجرد
686	divestiture	التصفية، التجريد
687	divestment	التصفية
688	divestments	التصفية
689	divests	يجرد، يتخلص، يتجرد
690	divorce	طلاق
691	divorced	منفصل
692	divulge	يفشي
693	divulged	يفشي، مُفشى
694	divulges	يفشي
695	divulging	يفشي
696	doubt	يشك، يشكك، يرتاب، الريب، التردد، الشك
697	doubted	يشك، يشكك، مشكوك به، مشكك به
698	doubtful	مبهم، متردد، مشكوك، غير مؤكد، موضع شك، محل شك
699	downgrade	يخفض، يقلل، التخفيض، التقليل
700	downgraded	يخفض، يقلل، مخفض

No.	English Word	Arabic Translation
701	downgrading	يخفض، يقلل، مخفض، التخفيض، التقليل
702	downsize	يخفض، يقلص، التخفيض، التقليص
703	downsized	يخفض، يقلص، التخفيض، التقليص، مخفض، منكمش
704	downsizes	يخفض، يقلص
705	downsizing	يخفض، يقلص، التخفيض، التقليص
706	downtime	التوقف، التعطل
707	downturn	الركود، الانكماش
708	downward	هابط
709	downwards	هابط
710	drag	يجر، يسحب، يعرقل
711	drastic	عنيف، حاد، قاسي
712	drastically	بشكل حاد، بنحو حاد، بصورة حادة، بطريقة حادة
713	drawback	عائق، عقبة، عيب
714	dropped	يتراجع، يهبط، ينخفض، متراجع، هابط، منخفض
715	drought	الجفاف، الشح
716	duress	يرغم، يجبر، الإرغام، الإجبار
717	dysfunction	عجز، قصور، خلل
718	dysfunctional	معطل، مختل، مضطرب
719	easing	يخفف، التخفيف
720	egregious	بشع، شنيع
721	egregiously	بشكل شنيع، بنحو شنيع، بشكل بشع، بنحو بشع
722	embargo	يقاطع، يحظر، يمنع، المقاطعة، الحظر، المنع
723	embargoed	يقاطع، يحظر، يمنع، ممنوع، محظور
724	embargoing	يقاطع، يحظر، يمنع، ممنوع، محظور، المقاطعة، الحظر، المنع
725	embarrass	يحرج
726	embarrassed	يحرج، محرج، مخجل
727	embarrasses	يحرج
728	embarrassing	يحرج، محرج، مخجل، الحرج
729	embarrassment	الإحراج
730	embezzle	يختلس، يسرق
731	embezzled	يختلس، يسرق، مختلس، مسروق
732	embezzlement	الأختلاس
733	embezzler	مختلس
734	embezzles	يختلس، يسرق
735	embezzling	يختلس، يسرق، مختلس، مسروق، الأختلاس
736	encroach	يتعدى، ينتهك
737	encroached	يتعدى، ينتهك
738	encroaches	يعتدي، ينتهك
739	encroaching	يعتدي، ينتهك، التعدي، الأنتهاك
740	encroachment	التعدي، الأنتهاك
741	encumber	يثقل
742	encumbered	يثقل
743	encumbering	يثقل
744	encumbers	يثقل
745	encumbrance	العبء
746	endanger	يهدد
747	endangered	يهدد
748	endangering	يهدد
749	endangerment	الخطر
750	endangers	يهدد
751	enjoin	يُلزم، يأمر
752	enjoined	يُلزم، يأمر

No.	English Word	Arabic Translation
753	enjoining	يُلزم، يأمر، الإلزام
754	enjoins	يُلزم، يأمر
755	erode	يتآكل
756	eroded	يتآكل، متاكل
757	erodes	يتآكل
758	eroding	يتآكل، متاكل
759	erosion	التآكل
760	erratic	متذبذب، متقلب
761	erratically	بشكل غير منتظم، بطريقة غير منتظمة، بصورة غير منتظمة، بنحو غير منتظم، بشكل متذبذب، بنحو متذبذب
762	erred	يخطئ
763	erring	يخطئ
764	erroneous	خاطئ، مغلوطة
765	erroneously	بشكل خاطئ، بنحو خاطئ، بصورة خاطئة، بشكل مغلوط، بنحو مغلوط، بصورة مغلوطة، بطريقة مغلوطة
766	error	خطأ
767	errs	يخطئ
768	escalate	يتفاقم، يصعد
769	escalated	يتفاقم، يصعد، متفاقم
770	escalates	يتفاقم، يصعد
771	escalating	يتفاقم، يصعد، التصعيد، المتفاقم
772	evade	يتهرب، يتملص، يراوغ
773	evaded	يتهرب، يتملص، يراوغ
774	evades	يتهرب، يتملص، يراوغ
775	evading	يتهرب، يتملص، يراوغ
776	evasion	التهرب، التملص، المراوغة
777	evasive	متهرب
778	evict	يطرد، يجلي
779	evicted	يطرد، يجلي، مطرود
780	evicting	يطرد، يجلي
781	eviction	الطرد، الإجلاء، الإخلاء
782	evicts	يطرد، يجلي
783	exacerbate	يستفحل، يتفاقم، يؤزم
784	exacerbated	يستفحل، يتفاقم، يؤزم
785	exacerbates	يستفحل، يتفاقم، يؤزم
786	exacerbating	يستفحل، يتفاقم، يؤزم
787	exacerbation	التأزيم
788	exaggerate	يضخم، يبالغ
789	exaggerated	يضخم، يبالغ
790	exaggerates	يضخم، يبالغ
791	exaggerating	يضخم، يبالغ
792	exaggeration	التضخيم، المبالغة
793	excessive	مفرط
794	excessively	بشكل مفرط، بنحو مفرط
795	exculpate	يبرئ
796	exculpated	يبرئ
797	exculpates	يبرئ
798	exculpating	يبرئ، براءة
799	exculpation	التبرئة
800	exculpatory	التبرئة
801	exonerate	يبرئ
802	exonerated	يبرئ

No.	English Word	Arabic Translation
803	exonerates	يبرئ
804	exonerating	يبرئ
805	exoneration	التبرئة
806	exploit	ينتهز
807	exploitation	الانتهاز
808	exploitative	انتهازي
809	exploited	ينتهز
810	exploiting	ينتهز، الانتهاز
811	expose	يفضح، يفشي، يعرض
812	exposed	يفضح، يفشي، يعرض
813	exposing	يفضح، يفشي، يعرض
814	expropriate	ينتزع، يصادر
815	expropriated	ينتزع، يصادر، منتزع، مصادر
816	expropriates	ينتزع، يصادر، منتزع، مصادر
817	expropriating	ينتزع، يصادر، منتزع، مصادر، المصادرة، الأنتزاع
818	expropriation	المصادرة، الأنتزاع
819	expulsion	الطرد
820	extenuating	تخفيفية
821	fail	يخفق، يفشل، يعجز
822	failed	يخفق، يفشل، يعجز
823	failing	يخفق، يفشل، يعجز، الإخفاق، الفشل، العجز
824	fails	يخفق، يفشل، يعجز
825	failure	الإخفاق، الفشل، العجز، القصور
826	fallout	التداعيات، العواقب، الفشل
827	false	مضلل، زائف، كاذب، خاطئ
828	falsely	بشكل خاطئ، بطريقة خاطئة، بنحو خاطئ، بشكل مزيف، بطريقة مزيفة، بنحو مزيف
829	falsification	التزييف، التزوير، التحريف
830	falsified	يزيف، يزور، يحرف، مزيف، مزور، محرف
831	falsifies	يزيف، يزور، يحرف
832	falsify	الكذب، التحريف، التزييف
833	falsifying	يزيف، يزور، يحرف، مزيف، مزور، محرف، التزييف، التزوير، التحريف
834	falsity	يزيف، يزور، يحرف
835	fatality	فاجعة، الوفاة
836	fatally	بشكل مدمر، بنحو مدمر، بشكل قاتل، بنحو قاتل
837	fault	يلوم، ينتقد، خطأ، عيب، خلل، قصور
838	faulted	يلوم، ينتقد
839	faulty	خاطئ
840	fear	يخاف، يخشى، الخوف، الخشية
841	felonious	إجرامِيّ
842	felony	جناية، جريمة
843	fictitious	زائف، كاذب
844	fines	يغرَّم، غرامات
845	fined	يغرَّم، مغرم
846	fired	مفصول، مطرود
847	firing	الإقالة
848	flaw	خلل، عيب
849	flawed	معتل
850	forbid	يمنع، يحرم، يحظر
851	forbidden	يمنع، يحرم، يحظر، ممنوع، محظور
852	forbidding	يمنع، يحرم، يحظر، ممنوع، محظور
853	forbids	يمنع، يحرم، يحظر
854	forced	يجبر، يضطر، يفرض، مجبر، مضطر

No.	English Word	Arabic Translation
855	forcing	يجبر، يضطر، يفرض، مجبر، مضطر
856	foreclose	ينزع، يصادر، حبس الرهن
857	foreclosed	ينزع، يصادر
858	forecloses	ينزع، يصادر
859	foreclosing	ينزع، يصادر
860	foreclosure	مصادر
861	forego	يتنازل عن، يتخلى عن، يستغني عن
862	foregoes	يتنازل عن، يتخلى عن، يستغني عن
863	foregone	متنازل عنه، مستغنى عنه
864	forestall	يستبق، يتحاشى
865	forestalled	يستبق، يتحاشى
866	forestalling	يستبق، يتحاشى
867	forestalls	يستبق، يتحاشى
868	forfeit	يفقد، ينسحب، يصادر
869	forfeited	يفقد، ينسحب، يصادر، مصادر
870	forfeiting	يفقد، ينسحب، يصادر، مصادر
871	forfeiture	المصادرة
872	forgers	مزور
873	forgery	التزوير
874	fraud	الأحتيال
875	fraudulence	الأحتيال
876	fraudulent	احتيالي، مزور، محتال
877	fraudulently	بشكل احتيالي، بنحو احتيالي، بطريقة احتيالية، بصورة احتيالية
878	frivolous	تافه، سطحي
879	frivolously	بطريقة سطحية، بنحو سطحي
880	frustrate	يحبط، يثبط
881	frustrated	يحبط، يثبط، محبط
882	frustrates	يحبط، يثبط
883	frustrating	يحبط، يثبط، محبط
884	frustratingly	بشكل محبط، بنحو محبط، بصورة محبطة، بطريقة محبطة
885	frustration	الإحباط
886	fugitives	هارب، فارّ
887	gratuitous	بلا داعي، بلا مبرر، بلا سبب، غير مبرر
888	gratuitously	بشكل غير مبرر، بنحو غير مبرر، بصورة غير مبرره، بطريقة غير مبرره
889	grievance	شكوى، تظلم
890	grossly	بشكل جسيم، بنحو جسيم، بشكل فادح، بنحو فادح
891	groundless	ليس مبرر، غير مبرر، عار من الصحة، لا أساس له، باطل، بلا أساس
892	guilty	مذنب، متورط
893	halt	يتعطل، يتوقف، متعطل، متوقف
894	halted	يتعطل، يتوقف، متعطل، متوقف
895	hamper	يكبح، يعيق، يعرقل
896	hampered	يكبح، يعيق، يعرقل
897	hampering	يكبح، يعيق، يعرقل، العرقلة
898	harass	يضايق، يزعج، يتحرش
899	harassed	يضايق، يزعج، يتحرش، مضايقة
900	harassing	يضايق، يزعج، يتحرش، مضايقة
901	harassment	المضايقة، التحرش
902	hardship	معاناة، ضائقة
903	harm	يضر، يؤذي، ضرر، أذى
904	harmed	يضر، يؤذي، متضرر
905	harmful	ضار، مضر، مؤذي

No.	English Word	Arabic Translation
906	harmfully	بشكل ضار، بنحو ضار، بصورة ضاره، بطريقة ضاره، بشكل مؤذي، بنحو مؤذي، بصورة مؤذية، بطريقة مؤذية
907	harming	يضر، يؤذي، ضرر، أذى
908	harsh	فظ، قسوة، قاسي، شدة
909	harsher	أقسى، أشد
910	harshest	الأشد، الأكثر شدة، الأقسى، الأكثر قسوة
911	harshly	شدة، قَسْوَة
912	harshness	الشدة، القسوة، الفظاظة، الخشونة
913	hazard	يخاطر، يجازف، خطر
914	hazardous	خطير
915	hinder	يعرقل، يعيق
916	hindered	يعرقل، يعيق
917	hindering	يعرقل، يعيق، إعاقة، عرقلة
918	hinders	يعرقل، يعيق
919	hindrance	الإعاقة، العرقلة
920	hostile	عدائي، معاد
921	hostility	العداء
922	hurt	يضر، يؤذي، الضرر، الأذى
923	hurting	يضر، يؤذي، الضرر، الأذى
924	idle	يتكاسل، تكاسل، خامل، معطل، متعطل
925	idled	يتكاسل، خامل، معطل
926	idling	يتكاسل، تكاسل، خامل، معطل، الخمول، التباطؤ
927	ignore	يهمل، يتجاهل، يغفل
928	ignored	يهمل، يتجاهل، يغفل، مهمل
929	ignores	يهمل، يتجاهل، يغفل
930	ignoring	يهمل، يتجاهل، يغفل، مهمل
931	ill	معتل
932	illegal	غير قانوني، محظور، مخالف للقانون
933	illegality	عدم المشروعية، عدم الشرعية، تجاوز القانون، انتهاك القانون
934	illegally	بشكل غير قانوني، بنحو غير قانوني، بصورة غير قانونية، بطريقة غير قانونية، غير قانوني، بصورة غير شرعية، بشكل مخالف للقانون، بنحو مخالف للقانون
935	illegible	مبهم، غير مقروء، صعب القراءة
936	illicit	محظور، غير قانوني، غير مشروع
937	illicitly	بشكل غير قانوني، بنحو غير قانوني، بصورة غير قانونية، بطريقة غير قانونية، بشكل مخالف للقانون، بنحو مخالف للقانون
938	illiquid	غير قابل للتداول
939	illiquidity	انخفاض السيولة، نقص السيولة، عدم كفاية السيولة، شح السيولة، عدم السيولة
940	imbalance	اختلال التوازن، عدم التوازن، انعدام التوازن
941	immature	غير ناضج، عدم النضج
942	immoral	غير أخلاقي، منافي للأخلاق، لاأخلاقي، غير أخلاقي
943	impair	يضعف، يتلف
944	impaired	يضعف، يتلف، يضر، متضرر، ضعيف
945	impairing	يضعف، يتلف، يضر، متضرر، ضعيف، الاعتلال، الضعف، التدهور
946	impairment	الاعتلال، الضعف، التدهور
947	impairs	يضعف، يتلف، يضر
948	impasse	مأزق، طريق مسدود
949	impede	يعيق، يعرقل
950	impeded	يعيق، يعرقل، عائق، معرقل
951	impedes	يعيق، يعرقل
952	impediment	العائق
953	impeding	يعيق، يعرقل، عائق، معرقل
954	impending	وشيك

No.	English Word	Arabic Translation
955	imperative	ملح، حتمي
956	imperfection	العيب، النقص
957	imperil	يعرض
958	impermissible	غير مسموح، غير مقبول
959	implicate	يورط
960	implicated	يورط، متورط
961	implicates	يورط
962	implicating	يورط، متورط
963	impossibility	الاستحالة
964	impossible	مستحيل
965	impound	يحجز، يصادر
966	impounded	يحجز، يصادر، محتجز، مصادر
967	impounding	يحجز، يصادر، محتجز، مصادر
968	impounds	يحجز، يصادر
969	impracticable	غير عملي، ليس عملي، غير واقعي، ليس واقعي، لا يمكن تطبيقة، غير قابل للتطبيق، غير قابل للتنفيذ
970	impractical	غير عملي، ليس عملي، غير واقعي، ليس واقعي
971	impracticality	عدم الواقعية
972	imprisonment	السحن، الأعتقال، الإيقاف الأمني
973	improper	غير ملائم، غير لائق، غير مناسب
974	improperly	بشكل غير ملائم، بنحو غير ملائم، بشكل غير لائق، بنحو غير ملائم
975	impropriety	البذاءة
976	imprudent	طائش، متهور
977	imprudently	بشكل طائش، بنحو طائش، بشكل متهور، بنحو متهور
978	inability	العجز، عدم القدرة
979	inaccessible	غير متاح، يتعذر الوصول إليه
980	inaccuracy	عدم الدقة
981	inaccurate	غير دقيق
982	inaccurately	بشكل غير دقيق، بنحو غير دقيق، بصورة غير دقيقة، بطريقة غير دقيقة
983	inaction	التراخي، الكسل
984	inactivate	يعطل
985	inactivated	يعطل، معطل
986	inactivates	يعطل
987	inactivating	يعطل
988	inactivation	التعطل
989	inactivity	التعطل
990	inadequacy	القصور، النقص، عدم الكفاية
991	inadequate	قاصر، غير كافي، غير مؤهل
992	inadequately	بشكل غير ملائم، بنحو غير ملائم، بشكل غير كافي، بنحو غير كافي
993	inadvertent	غافل، غير مقصود، غير متعمد، خطأ غير مقصود، عن غير قصد
994	inadvertently	غير مقصود، بشكل غير مقصود، بشكل غير متعمد، عن غير قصد، بدون قصد
995	inadvisability	عدم الملاءمة، عدم الجدارة بالنصح
996	inadvisable	غير موصى به، غير مرغوب فيه، غير مستحسن، غير مناسب
997	inappropriate	غير ملائم، غير لائق، غير مناسب
998	inappropriately	بشكل غير ملائم، بشكل غير لائق، بشكل غير مناسب، بطريقة غير مقبولة، بصورة غير مناسبة
999	inattention	عدم الانتباه، عدم التركيز، عدم الاكتراث
1000	incapable	عاجز، محدود القدرة
1001	incapacitated	عاجز، غير قادر
1002	incapacity	العجز، عدم القدرة
1003	incarcerate	يسجن، يحتجز
1004	incarcerated	يسجن، يحتجز، سجين، محتجز

No.	English Word	Arabic Translation
1005	incarcerates	يسجن، يحتجز
1006	incarcerating	يسجن، يحتجز ، سجين، محتجز
1007	incarceration	السجن، الحجز
1008	incidence	حادث
1009	incident	حادث
1010	incompatibility	عدم الانسجام، عدم التوافق، التعارض، التضارب
1011	incompatible	متضارب، متعارض، غير منسجم، ليس منسجم
1012	incompetence	قصور الأداء، عدم الكفاءة
1013	incompetency	القصور، عدم الكفاءة
1014	incompetent	عاجز، عديم الكفاءة، غير مؤهل، غير كفؤ
1015	incompetently	بشكل غير مكتمل، بشكل غير كفؤ، بشكل غير ماهر، بلا كفاءة
1016	incomplete	ناقص، غير مكتمل
1017	incompletely	بشكل غير مكتمل، بشكل منقوص، بشكل ناقص، بشكل غير كامل
1018	incompleteness	النقص
1019	inconclusive	غير حاسم، متردد، غير مؤكد، غير مقنع، غير قاطع
1020	inconsistency	عدم الأتساق، عدم التناسق، التناقض، عدم الثبات
1021	inconsistent	غير متسق، غير ثابت
1022	inconsistently	بشكل متناقض، بنحو متناقض، بشكل غير ثابت، بنحو غير ثابت، بشكل غير متسق، بنحو غير متسق، بشكل متضارب، بنحو متضارب
1023	inconvenience	المشقة، عدم الراحة
1024	inconvenient	متعب، غير مريح
1025	incorrect	خاطئ، مغلوط، غير صحيح
1026	incorrectly	،بشكل خاطئ، نحو خاطئ، بشكل غير دقيق، بنحو غير دقيق، بشكل مغلوط، بنحو مغلوط بشكل غير صحيح، بنحو غير صحيح
1027	incorrectness	عدم الصحة
1028	indecency	الوقاحة، البذاءة
1029	indecent	وقح، بذيء
1030	indefeasible	لا يمكن دحضه، غير قابل للإبطال، غير قابل للإلغاء، غير قابل للنقض
1031	indefeasibly	غير قابل للإبطال، لا يمكن دحضه، لا يمكن إلغاؤه، لا يمكن تحمله، غير قابل للنقض، غير قابل للإلغاء
1032	indict	يتهم، يقاضي، يوجه اتهام
1033	indictable	عرضة للمقاضاة، عرضة للاتهام، مستوجب للملاحقة القضائية
1034	indicted	متهم
1035	indicting	المقاضاة
1036	indictment	لائحة الأتهام، دعوى قضائية، الإدانة، المقاضاة
1037	ineffective	عديم الفائدة، غير مجد، غير فعّال، عديم الجدوى
1038	ineffectively	بشكل غير فعال، بنحو غير فعال، بشكل غير مجد، بنحو غير مجدي
1039	ineffectiveness	عدم الجدوى، عدم الفعالية، عديم الفائدة، عدم الكفاءة
1040	inefficiency	عدم الفعالية، عدم الكفاءة، القصور
1041	inefficient	غير كفؤ، غير فعّال
1042	inefficiently	بشكل غير كفؤ، بشكل غير فعال، بنحو غير فعال
1043	ineligibility	عدم الأهلية، عدم الجدارة، غير مؤهل، عدم الاستحقاق
1044	ineligible	عديم الأهلية، غير مؤهل، عديم الجدارة
1045	inequitable	مجحف، جائر، غير منصف
1046	inequitably	بشكل غير عادل، بنحو غير عادل، بشكل ظالم، بنحو ظالم، بشكل جائر، بنحو جائر، بشكل غير منصف، بنحو غير منصف
1047	inequity	الاجحاف، عدم المساواة
1048	inevitable	حتمي
1049	inexperience	قله الخبره، عدم الخبرة
1050	inexperienced	قليل الخبرة، غير متمرس، عديم الخبرة
1051	inferior	رديء، دون المستوى
1052	inflicted	يصاب

No.	English Word	Arabic Translation
1053	infraction	الخرق، المخالفة، الإنتهاك
1054	infringe	ينتهك، يخرق، يخرق
1055	infringed	ينتهك، يخرق، منتهك، خرق
1056	infringement	الانتهاك، التعدي
1057	infringes	ينتهك، يخرق، يخرق
1058	infringing	الانتهاك، التعدي
1059	inhibited	يثبط، يكبت، مثبط
1060	inimical	عدائي، معادي
1061	injunction	أمر قضائي، إنذار قضائي
1062	injure	يجرح، يؤذي، يصيب
1063	injured	يجرح، يؤذي، يصيب
1064	injures	يجرح، يؤذي، يصيب
1065	injuring	يجرح، يؤذي، يصيب، مجروح، مصاب، الإصابة
1066	injurious	ضار، مضر، مؤذي
1067	injury	الأذى، الضرر، الإصابة
1068	inordinate	مبالغ فيه، مغالي، مفرط
1069	inordinately	بشكل مفرط، بنحو مفرط، بصورة مفرطة
1070	inquiry	التحري، استقصاء، استفسار
1071	insecure	قلق، غير مستقر، غير آمن
1072	insensitive	متبلد، ليس مبالي، غير مبالي، لا مبالي
1073	insolvency	عجز عن السداد، إعسار، إفلاس
1074	insolvent	عاجز عن الدفع، مفلس، معسر
1075	instability	التقلب، انعدام الأستقرار، عدم الأستقرار، الأضطراب
1076	insubordination	التمرد، العِصيان، تجاوز الأوامر
1077	insufficiency	القصور، عدم الكفاية
1078	insufficient	ضئيل، غير كاف
1079	insufficiently	،بشكل غير مكتمل، بنحو غير مكتمل، بشكل ناقص، بشكل غير ملائم، بنحو غير ملائم بشكل غير كاف، بنحو غير كافي
1080	insurrection	التمرد
1081	intentional	متعمد
1082	interfere	يتدخل، يتعارض، يتصادم
1083	interfered	يتدخل، يتعارض، يتصادم، متعارض، متدخل
1084	interference	التدخل، التعارض، التصادم
1085	interferes	يتدخل، يتعارض، يتصادم
1086	interfering	التدخل، التعارض، التصادم
1087	intermittent	متقطع
1088	intermittently	على فترات متقطعة، بشكل غير مستمر، بنحو غير مستمر، بشكل متقطع، بنحو متقطع
1089	interrupt	يقطع، يعوق، يعطل
1090	interrupted	يقطع، يعوق، يعطل، منقطع، مقطوع
1091	interrupting	يقطع، يعوق، يعطل، منقطع، مقطوع، الأنقطاع، الإعاقه، التعطل
1092	interruption	الأنقطاع، الإعاقه، التعطل
1093	intimidation	التهديد، الترهيب
1094	intrusion	الاختراق، التسرب، الاقتحام
1095	invalid	باطل، لاغي، غير قانوني، غير صحيح
1096	invalidate	يُبطل، يعطل
1097	invalidated	يُبطل، يعطل، معطل
1098	invalidates	يُبطل، يعطل
1099	invalidating	يُبطل، يعطل
1100	invalidation	إبطال
1101	invalidity	البطلان
1102	investigate	يتحرى، يتقصى، يستقصي
1103	investigated	يتحرى، يتقصى، يستقصي

No.	English Word	Arabic Translation
1104	investigates	يتحري، يتقصى، يستقصي
1105	investigating	يتحري، يتقصى، يستقصي
1106	investigation	التحري، الأستقصاء
1107	involuntarily	بشكل إلزامي، بنحو إلزامي
1108	involuntary	إلزامي، قسري، إجباري
1109	irreconcilable	لا يعوض، غير قابل للتعويض
1110	irrecoverable	لا يمكن تعويضه، غير قابل للاسترداد، غير قابل للاستعادة، لا يمكن استرداده، متعذر إصلاحه
1111	irrecoverably	غير قابل للاسترداد، لا يمكن استرداده
1112	irregular	غير منتظم، غير مألوف، غير عادي
1113	irregularity	عدم الأنتظام
1114	irregularly	بشكل غير منتظم، بنحو غير منتظم، بشكل ليس منتظم، بنحو ليس منتظم
1115	irreparable	لا يمكن إصلاحه، متعذر إصلاحه
1116	irreversible	لا رجعة فيه، لا يمكن تغييره
1117	jeopardize	يهدد
1118	jeopardized	يهدد
1119	justifiable	مبرر، قابل للتبرير
1120	kickback	رشوة
1121	knowingly	بنحو متعمد، بشكل متعمد
1122	lack	شح، قلة، ندرة
1123	lacked	يفتقر
1124	lacking	يفتقر، مفتقر، افتقار
1125	lackluster	شاحِب، باهت
1126	lag	التأخر
1127	lagged	متأخر عن
1128	lagging	التأخر
1129	lapse	ينقضي، هفوة، تراخي، خطأ، سقوط
1130	lapsed	ينقضي
1131	lapsing	ينقضي
1132	laundering	غسيل الأموال، تبييض الأموال
1133	layoff	الفَصل، التسريح
1134	lie	يكذب، الكذب
1135	limitation	قصور
1136	lingering	مزمن
1137	liquidate	يصفي، يسيل
1138	liquidated	يصفي، يسيل
1139	liquidates	يصفي، يسيل
1140	liquidating	يصفي، يسيل
1141	liquidation	التصفية
1142	liquidator	مصفي
1143	litigant	مدعي، متقاضي، مدعى عليه
1144	litigate	يتخاصَم، يقاضي
1145	litigated	يتخاصَم، يقاضي، تمت مقاضاته
1146	litigates	يقاضي
1147	litigating	يقاضي، متقاضي، مدعى عليه، التقاضي، المقاضاة
1148	litigation	التقاضي، المقاضاة
1149	lockout	الإغلاق
1150	lose	يخسر، يفقد، يضيع، ينهزم، الخسارة
1151	loses	يخسر، يفقد، يضيع، ينهزم
1152	losing	يخسر، يفقد، يضيع، ينهزم، الخسارة
1153	loss	الخسارة، الهزيمة
1154	lost	يخسر، يفقد، يضيع، ينهزم، خاسر

No.	English Word	Arabic Translation
1155	lying	يكذب، كاذب، الكذب
1156	malfeasance	سوء السلوك، سوء التصرّف
1157	malfunction	التعطل
1158	malfunctioned	متعطل
1159	malfunctioning	عطل، قصور
1160	malice	حقد، خبث
1161	malicious	حاقد، خبيث، مغرض
1162	maliciously	بنية إلحاق الضرر، بسوء نية، بقصد إلحاق الضرر
1163	malpractice	إهمال مهني، سوء استخدام السلطة
1164	manipulate	يتلاعب
1165	manipulated	يتلاعب
1166	manipulates	يتلاعب
1167	manipulating	يتلاعب، التلاعب
1168	manipulation	التلاعب
1169	manipulative	تلاعبي، استغلالي
1170	markdown	تقليل القيمة، تخفيض السعر، تخفيض القيمة
1171	markdowns	تقليل القيمة، تخفيض السعر، تخفيض القيمة
1172	misapplication	إساءة التطبيق، إساءة الإستعمال
1173	misapplied	يسيء تطبيق، يسئ الاستعمال، يخطئ في تطبيق، إساءة التطبيق، إساءة الإستعمال
1174	misapplies	يسيء تطبيق، يسئ الاستعمال، يخطئ في تطبيق
1175	misapply	يسئ الاستعمال، يسئ التطبيق
1176	misapplying	يسئ الاستعمال، يسئ التطبيق، إساءة التطبيق، إساءة الإستعمال
1177	misappropriate	يختلس
1178	misappropriated	يختلس، مختلس
1179	misappropriates	يختلس
1180	misappropriating	يختلس، مختلس، الاختلاس
1181	misappropriation	الاختلاس
1182	misbranded	غش، ضلل
1183	miscalculate	يخطئ في حساب، يخطئ في تقدير
1184	miscalculated	يخطئ في حساب، يخطئ في تقدير
1185	miscalculates	يخطئ في حساب، يخطئ في تقدير
1186	miscalculating	يخطئ في حساب، يخطئ في تقدير
1187	miscalculation	حساب غير دقيق، سوء تقدير، تقدير خاطئ
1188	mischaracterization	تفسير خاطئ، توصيف خاطئ
1189	mischief	الأذى، الضرر
1190	misclassification	الترتيب غير الدقيق، الترتيب الخطأ، التقسيم غير صحيح، التصنيف الخاطئ
1191	misclassified	يخطى في ترتيب، يخطئ في تقسيم، يخطئ في التقسيم، يخطئ في التصنيف، مصنف خطأ
1192	misclassify	يخطى في ترتيب، يخطئ في تقسيم، يخطئ في التقسيم، يخطئ في التصنيف
1193	miscommunication	سوء الفهم، سوء الأتصال، خلل في التواصل، سوء التفاهم
1194	misconduct	سوء السلوك، إساءة السلوك
1195	misdated	مؤرخ بشكل خاطئ
1196	misdemeanor	جنحة
1197	misdirected	يضلل، سوء توجيه
1198	mishandle	يسئ المعاملة، يسئ الإدارة، يسيء التصرف، إساءة المعاملة، إساءة الإدارة، إساءة التصرف، إساءة التعامل، سوء التعامل، سوء التصرف، التدبير الخاطئ، التعامل السيء
1199	mishandled	يسئ المعاملة، يسئ الإدارة، يسيء التصرف، معاملة سيئة
1200	mishandles	يسئ المعاملة، يسئ الإدارة، يسيء التصرف
1201	mishandling	،يسئ المعاملة، يسئ الإدارة، يسيء التصرف، معاملة سيئة، إساءة المعاملة، إساءة الإدارة إساءة التصرف، إساءة التعامل، سوء التعامل، سوء التصرف، التدبير الخاطئ، التعامل السيء
1202	misinform	يضلل، يخدع

No.	English Word	Arabic Translation
1203	misinformation	،بيانات مغلوطة، بيانات مُضللة، بيانات خاطئة، معلومات مغلوطة، معلومات مُضللة معلومات خاطئة
1204	misinformed	يضلل، يخدع، مضللة
1205	misinforming	يضلل، يخدع، بيانات مغلوطة، بيانات مُضللة، بيانات خاطئة، معلومات مغلوطة، معلومات مُضللة، معلومات خاطئة
1206	misinforms	يضلل، يخدع
1207	misinterpret	يسيء تفسير، يسئ فهم
1208	misinterpretation	إساءة التفسير، سوء الفهم، إساءة التفسير، إساءة الفهم، التأويل الخاطئ، التفسير خاطئ
1209	misinterpreted	يسيء تفسير، يسئ فهم
1210	misinterpreting	يسيء تفسير، يسئ فهم، إساءة التفسير، إساءة الفهم، التأويل الخاطئ، التفسير خاطئ
1211	misinterprets	يسيء تفسير، يسئ فهم
1212	misjudge	يُخطئ في الحكم، يسئ الحكم، يسئ التقدير، يحكم بشكل خاطئ، يقدر بشكل خاطئ
1213	misjudged	يُخطئ في الحكم، يسئ الحكم، يسئ التقدير، يحكم بشكل خاطئ، يقدر بشكل خاطئ
1214	misjudges	يُخطئ في الحكم، يسئ الحكم، يسئ التقدير، يحكم بشكل خاطئ، يقدر بشكل خاطئ
1215	misjudging	يُخطئ في الحكم، يسئ الحكم، يسئ التقدير، يحكم بشكل خاطئ، يقدر بشكل خاطئ
1216	misjudgment	إساءة الحكم، إساءة التقدير، سوء الحكم، سوء التقدير، إساءة التقدير، الحكم الخاطئ، سوء الحكم، التقدير خاطئ
1217	mislabel	يُسيء التسمية
1218	mislabeled	يُسيء التسمية، مُصنف بشكل خطأ، موصوف بشكل خاطئ، خطأ في التصنيف، توصيف خاطئ
1219	mislabeling	يُسيء التسمية، مُصنف بشكل خطأ، موصوف بشكل خاطئ، خطأ في التصنيف، توصيف خاطئ
1220	mislabelled	تسمية خاطئة، مُصنف خطأ، مُسمى خطأ، موصوف بشكل خاطئ، أساء التسمية، تصنيف خاطئ
1221	mislabels	يُسيء التسمية
1222	mislead	يضلل، يخدع، يضلل، سوء التعامل
1223	misleading	يضلل، يخدع، يضلل، سوء التعامل
1224	misleadingly	بشكل مضلل، بنحو مضلل، بشكل خادع، بنحو خادع
1225	misleads	يضلل، يخدع، يضلل
1226	misled	يضلل، يخدع، يضلل
1227	mismanage	يخفق في إدارة، يسئ إدارة، يسئ تدبير، يخفق في إدارة
1228	mismanaged	يخفق في إدارة، يسئ إدارة، يسئ تدبير، يخفق في إدارة، سوء الإدارة
1229	mismanagement	سوء الإدارة، الفشل إداري، سوء التدبير، التقصير الإداري، الأهمال إداري
1230	mismanages	يخفق في إدارة، يسئ إدارة، يسئ تدبير، يخفق في إدارة
1231	mismanaging	يخفق في إدارة، يسئ إدارة، يسئ تدبير، يخفق في إدارة، سوء الإدارة، الفشل إداري، سوء التدبير، التقصير الإداري، الأهمال إداري
1232	mismatch	غير متطابق
1233	mismatched	غير متطابق
1234	mismatching	غير متطابق
1235	misplaced	يضيع، مفقود، ضائع
1236	misprice	يخطئ في تسعير، يسعر بشكل خاطئ، خلل في التسعير، التسعير الخاطئ، خطأ في التسعير، التسعير الخاطئ، سوء التسعير
1237	mispricing	يخطئ في تسعير، يسعر بشكل خاطئ، خلل في التسعير، التسعير الخاطئ، خطأ في التسعير، التسعير الخاطئ، سوء التسعير
1238	mispricings	يخطئ في تسعير، يسعر بشكل خاطئ
1239	misrepresent	يُحرّف، يخدع، يضلل
1240	misrepresentation	التحريف، الخداع، التضليل
1241	misrepresented	يُحرّف، يخدع، يضلل، مغلوط، محرف
1242	misrepresenting	يُحرّف، يخدع، يضلل، مغلوط، محرف، التحريف، الخداع، التضليل
1243	misrepresents	يُحرّف، يخدع، يضلل
1244	miss	يفوت
1245	missed	ضائعة، يخطئ، فائِت

No.	English Word	Arabic Translation
1246	misstate	يشوه، يُحرّف
1247	misstated	يشوه، يُحرّف، محرف، مشوه
1248	misstatement	تصريح غير صحيح، تصريح خاطئ، بيان كاذب، إعلان كاذب، إفادة غير صحيحة
1249	misstates	يشوه، يُحرّف، يشوه، يصرح بشكل خاطئ، يعلن بشكل خاطئ
1250	misstating	يشوه، يُحرّف، محرف، مشوه
1251	misstep	يتعثر، خطأ، إخفاق، غلطة
1252	mistake	يخطئ، يغلط، خطأ، غلطة، سوء فهم
1253	mistaken	يخطئ، يغلط، مخطئ، خاطئ، مغلوط
1254	mistakenly	بشكل خاطئ، بنحو خاطئ، بشكل مخطئ، بنحو مخطئ، عن طريق الخطأ
1255	mistaking	يخطئ، يغلط، مخطئ، خاطئ، مغلوط
1256	mistrial	محاكمة ملغاة، محاكمة باطلة
1257	misunderstand	يسئ فهم، يخطئ فهم
1258	misunderstanding	يسئ فهم، يخطئ فهم، سوء الفهم، سوء في الفهم
1259	misunderstood	يسئ فهم، يخطئ فهم، سوء الفهم، سوء في الفهم
1260	misuse	يسئ استعمال، يسئ استخدام، استغلال خاطئ، إساءة استعمال، إساءة استخدام، سوء استعمال، سوء استخدام
1261	misused	يسئ استعمال، يسئ استخدام
1262	misusing	يسئ استعمال، يسئ استخدام، استغلال خاطئ، إساءة استعمال، إساءة استخدام، سوء استعمال، سوء استخدام
1263	monopolists	محتكر
1264	monopolistic	محتكر، احتكاري
1265	monopolization	الاحتكار
1266	monopolize	يحتكر
1267	monopolized	يحتكر، محتكر
1268	monopolizes	يحتكر
1269	monopolizing	يحتكر، الاحتكار
1270	monopoly	الاحتكار
1271	moratorium	الحظر، التجميد، فرض حظر
1272	mothballed	يجمد، يعطل
1273	mothballing	يجمد، يعطل، متجمد، متعطل، التجميد، التعطل
1274	negative	سلبي
1275	negatively	بشكل سلبي، بنحو سلبي
1276	neglect	يغفل، يهمل، يتهاون
1277	neglected	يغفل، يهمل، متهاون، مهمل
1278	neglectful	مهمل، لا مبال، غير مبالي
1279	neglecting	يغفل، يهمل، يتهاون
1280	negligence	الإهمال، التقصير، التهاون
1281	negligent	مهمل، متهاون، غير مبالي
1282	negligently	بشكل متهاون، بنحو متهاون، بشكل غير مبالي، بنحو غير مبالي
1283	noncompetitive	خالٍ من المنافسة، غير تنافسي، احتكاري
1284	noncompliance	عدم الالتزام، عدم المطابقة، عدم الامتثال
1285	noncompliant	غير مطابق
1286	noncomplying	غير مطابق
1287	nonconforming	غير مطابق، عدم التوافق
1288	nonconformity	عدم المطابقة، عدم التوافق
1289	nondisclosure	حجب المعلومات، عدم الإفصاح
1290	nonfunctional	متعطل، معطل، عاطل، خارج الخدمة
1291	nonpayment	تقصير في السداد، تخلف عن الدفع، عدم الدفع، عدم سداد
1292	nonperformance	عدم الاستجابة، فشل في الأداء، تقصير في الأداء
1293	nonperforming	غير فعّال، متعثر، غير مثمر
1294	nonproducing	غير منتج، غير مثمر، غير مفيد
1295	nonproductive	غير فعّال، غير مُربح، غير منتج، غير مثمر

No.	English Word	Arabic Translation
1296	nonrecoverable	لا يمكن استعادته، لا يمكن تحصيله، لا يمكن استرجاعه، غير قابل للاسترداد
1297	nonrenewal	عدم التجديد
1298	nuisance	أذى، ازعاج
1299	nullification	إبطال، النقض
1300	nullified	يبطل، يلغي، ملغى
1301	nullifies	يُبطل، يلغي
1302	nullify	يبطل، يلغي
1303	nullifying	يبطل، يلغي، بطلان، إبطال
1304	objected	يعترض، يرفض، معترض
1305	objecting	يعترض، يرفض، معترض، الاعتراض
1306	objection	الاعتراض، الاحتجاج
1307	objectionable	مرفوض، غير مقبول
1308	objectionably	بشكل مرفوض، بنحو مرفوض، بشكل غير مقبول، بنحو غير مقبول
1309	obscene	فاحش، دنيء، بغيض، بذيء
1310	obscenity	الفحش، البذاءة
1311	obsolescence	التقادم
1312	obsolete	بائد
1313	obstacle	عقبة، عائق
1314	obstruct	يعرقل، يعيق، يحجب
1315	obstructed	يعرقل، يعيق، يحجب، مسدود
1316	obstructing	يعرقل، يعيق، يحجب، عرقلة
1317	obstruction	العرقلة
1318	offence	إساءة، إهانة
1319	offend	يسيء
1320	offended	يسيء
1321	offender	مسيء، الجاني
1322	offending	يسيء، مسيء، المذنب
1323	offends	يسيء
1324	omission	الإغفال، الإهمال، الحذف
1325	omit	يسقط، يهمل، يغفل، يحذف
1326	omits	يسقط، يغفل، يهمل، يحذف
1327	omitted	يسقط، يغفل، يهمل، يحذف، مهملة
1328	omitting	يسقط، يغفل، يهمل، يحذف، مهملة، الإغفال، الإهمال، الحذف
1329	onerous	شاق، مرهق
1330	opportunistic	انتهازي
1331	opportunistically	بشكل انتهازي، بنحو انتهازي
1332	oppose	يعترض، يمانع
1333	opposed	يعترض، يمانع، معارض
1334	opposes	يعترض، يمانع
1335	opposing	يعترض، يمانع، معارض
1336	opposition	المعارض
1337	outage	عطل، انقطاع
1338	outdated	مهجور، قديم
1339	outmoded	مهجور
1340	overage	فائض
1341	overbuild	يتجاوز في بناء، يفرط في إنشاء، يبالغ في البناء، مبالغة في البناء، الإفراط في البناء
1342	overbuilding	يتجاوز في بناء، يفرط في إنشاء، يبالغ في البناء، مبالغة في البناء، الإفراط في البناء
1343	overbuilds	يتجاوز في بناء، يفرط في إنشاء، يبالغ في البناء
1344	overbuilt	مبالغة في البناء، يتجاوز في البناء، مبالغة في البناء
1345	overburden	يثقل، عبء زائد، مثقل
1346	overburdened	يثقل، مثقل
1347	overburdening	يثقل، عبء زائد، مثقل، الإثقال

No.	English Word	Arabic Translation
1348	overcapacities	قدرات زائدة، طاقات زائدة، فائض القدرات، فائض الطاقة
1349	overcapacity	القدرة الزائدة، طاقة زائدة، فائض القدرات، فائض الطاقة
1350	overcharge	يبالغ، يغالي، رسوم زائدة
1351	overcharged	يبالغ، يغالي
1352	overcharging	مغالاة
1353	overcome	يتصدى، يتغلب
1354	overcomes	يتصدى، يتغلب
1355	overcoming	يتصدى، يتغلب
1356	overdue	تأخر السداد، مبلغ مستحق، تأخر، متأخر
1357	overestimate	يبالغ، يغالي
1358	overestimated	مبالغ فيه، بالغ، مبالغ في تقديره
1359	overestimating	مبالغة في تقدير، مغالاة
1360	overestimation	المبالغة، مبالغة في التقدير
1361	overload	يثقل، عبء زائد، تحميل زائد، حمولة الزائدة، تحميل الزائد، زيادة التحميل
1362	overloaded	يثقل
1363	overloading	يثقل، عبء زائد، تحميل زائد، حمولة الزائدة، تحميل الزائد، زيادة التحميل
1364	overlook	يتجاهل، يتغاضى، يغفل، التجاهل
1365	overlooked	يتجاهل، يتغاضى، يغفل
1366	overlooking	يتجاهل، يتغاضى، يغفل، التجاهل
1367	overpaid	يدفع زيادة
1368	overpayment	دفع زائدة
1369	overproduced	يفرط في إنتاج، فائض الإنتاج
1370	overproduces	يفرط في إنتاج
1371	overproducing	الإنتاج الزائد، إفراط في الإنتاج
1372	overproduction	الإنتاج مفرط، فائض إنتاج، الإنتاج الزائد، أخفى، حجب
1373	overrun	يفيض عن، إعتام، إخفاء
1374	overrunning	يفيض عن، يغطي، يعتم، يظلل
1375	overshadow	يخفي، يحجب
1376	overshadowed	يخفي، يحجب
1377	overshadowing	يخفي، يحجب
1378	overshadows	يخفي، يحجب
1379	overstate	يبالغ، يغالي
1380	overstated	يبالغ، مغالى به، مبالغ فيه
1381	overstatement	مبالغة، تهويل
1382	overstates	يبالغ، يغالي
1383	overstating	المبالغة
1384	oversupplied	فائض العرض، فائض في العرض، فائض التموين
1385	oversupply	فائض العرض، فائض في العرض، فائض التموين
1386	oversupplying	فائض العرض، فائض في العرض، فائض التموين
1387	overtly	بشكل علني
1388	overturn	يسقط، يلغي، يبطل، يفسخ
1389	overturned	يسقط، يلغي، يبطل، يفسخ، ملغي
1390	overturning	يسقط، يلغي، يبطل، يفسخ
1391	overvalue	يبالغ في تقييم، يبالغ في تقدير، يبالغ في تثمين، يفرط في تقييم، يفرط في تقييم، يفرط في تثمين
1392	overvalued	يبالغ في تقييم، يبالغ في تقدير، يبالغ في تثمين، يفرط في تقييم، يفرط في تقييم، يفرط في تثمين، مبالغ في قيمته، مُغالى في تقديره، مُفرَط في التقييم، المبالغة في القيمة
1393	overvaluing	يبالغ في تقييم، يبالغ في تقدير، يبالغ في تثمين، يفرط في تقييم، يفرط في تقييم، يفرط في تثمين، مبالغ في قيمته، مُغالى في تقديره، مُفرَط في التقييم، المبالغة في القيمة
1394	panic	فزع، هلع، ذعر، ارتباك
1395	penalize	يعاقب، يغرم
1396	penalized	يعاقب، يغرم، معاقب

No.	English Word	Arabic Translation
1397	penalizes	يعاقب، يغرم
1398	penalizing	يعاقب، يغرم، المعاقبة
1399	penalty	عقاب، غرامة، عقوبه
1400	peril	خطر
1401	perjury	حنث، شهادة زور، كذب تحت القسم، إدلاء بشهادة كاذبة
1402	perpetrate	يقترف، يرتكب
1403	perpetrated	يقترف، يرتكب
1404	perpetrates	يقترف، يرتكب
1405	perpetrating	يقترف، يرتكب
1406	perpetration	اقتراف، ارتكاب
1407	persist	يلح
1408	persisted	يلح
1409	persistence	ألحاح
1410	persistent	ملح
1411	persistently	بشكل ملح، بنحو ملح
1412	persisting	يلح
1413	persists	يلح
1414	pervasive	متفشي
1415	pervasively	نحو متفشي، بشكل متفشي
1416	pervasiveness	التفشي
1417	petty	تافه
1418	picket	يحتج
1419	picketed	يحتج، محتج
1420	picketing	يحتج، محتج، احتجاج
1421	plaintiff	المدّعي
1422	plea	إلتماس، التوسل
1423	plead	يلتمس، يتوسل
1424	pleaded	يلتمس، يتوسل
1425	pleading	يلتمس، يتوسل
1426	pleads	يلتمس، يتوسل
1427	pled	يلتمس، يتوسل
1428	poor	سوء، فقير، رديء
1429	poorly	بشكل سيء، بنحو سيء، بشكل رديء، نحو رديء
1430	poses	يربك
1431	posing	يربك، إرباك
1432	postpone	يؤجل، يرجئ، يعلّق
1433	postponed	يؤجل، يرجئ، يعلّق، مؤخر، مؤجل
1434	postponement	التأجيل
1435	postpones	يؤجل، يرجئ، يعلّق
1436	postponing	يؤجل، يرجئ، يعلّق، مؤخر، مؤجل، التأجيل
1437	precipitated	يتعجل، متهور، متعجل
1438	precipitous	متهور، متعجل
1439	precipitously	بشكل متعجل، بنحو متعجل
1440	preclude	يعيق
1441	precluded	يعيق
1442	precludes	يعيق
1443	precluding	يعيق
1444	predatory	جشع
1445	prejudice	يتحيز، يجحف، التحيز، الإحجاف
1446	prejudiced	يتحيز، يجحف، متحيز، مجحف، الإحجاف
1447	prejudicial	متحيز
1448	prejudicing	يتحيز، يجحف، متحيز، مجحف، الإحجاف، التحيز

No.	English Word	Arabic Translation
1449	premature	سابق لأوانه، غير ناضج
1450	prematurely	بصورة متعجلة، بشكل متعجل
1451	pressing	ملح
1452	pretrial	قبل المحاكمة، ما قبل التقاضي
1453	preventing	يحترز، يتجنب
1454	prevention	التحوط
1455	prevents	يمنع
1456	problem	إشْكال، عقبة، مشكلة
1457	problematic	إشْكال
1458	problematical	إشْكال
1459	prolong	يطيل
1460	prolongation	إطالة
1461	prolonged	يطيل، مطول
1462	prolonging	يطيل، إطالة
1463	prolongs	يطيل
1464	prone	معرض
1465	prosecute	يقاضي
1466	prosecuted	يقاضي
1467	prosecutes	يقاضي
1468	prosecuting	يقاضي
1469	prosecution	محاكمة، مقاضاة
1470	protest	يحتج، احتجاج
1471	protested	يحتج
1472	protester	محتج
1473	protesting	يحتج، محتج، احتجاج
1474	protestor	يحتج، محتج
1475	protestors	محتج
1476	protracted	يطيل، مطول
1477	protraction	إطالة
1478	provoke	يستفز، يحرض، التحريض، الاستفزاز
1479	provoked	يستفز، يحرض
1480	provokes	يستفز، يحرض
1481	provoking	يستفز، يحرض، التحريض، الاستفزاز
1482	punished	يعاقب، معاقب
1483	punishes	يعاقب
1484	punishing	يعاقب، معاقب
1485	punishment	عقاب
1486	punitive	تأديبي
1487	purport	يزعم، يوهم
1488	purported	يزعم، يوهم
1489	purportedly	بشكل مزعوم
1490	purporting	يزعم، يوهم
1491	question	يستجوب، يسأل، تساؤل، يتساءل، يشكك
1492	questionable	مشكوك فيه، محل تساؤل، محل شك، موضع شك، موضع تساؤل
1493	questionably	بشكل مشكوك به
1494	questioned	يستجوب، يسأل، تساؤل، يتساءل، يشكك
1495	questioning	يستجوب، يسأل، تساؤل، يتساءل، يشكك
1496	quit	يستقيل، يترك
1497	quitting	يستقيل، يترك، استقالة
1498	racketeer	يحتال، محتال
1499	racketeering	يحتال، محتال، احتيال، الاحتيال المالي
1500	rationalization	ترشيد

No.	English Word	Arabic Translation
1501	rationalize	يرشِّد
1502	rationalized	يرشِّد
1503	rationalizes	يرشِّد
1504	rationalizing	يرشِّد، ترشيد
1505	reassessment	إعادة تقييم، إعادة تقدير
1506	reassign	يعيد تخصيص، يعيد تعيين، يعيد تكليف
1507	reassigned	يعيد تخصيص، يعيد تعيين، يعيد تكليف
1508	reassigning	يعيد تخصيص، يعيد تعيين، يعيد تكليف، إعادة تعيين، إعاد تكليف، إعادة تخصيص
1509	reassignment	إعادة تعيين، إعاد تكليف، إعادة تخصيص
1510	reassigns	يعيد تخصيص، يعيد تعيين، يعيد تكليف، يعيد توزيع
1511	recall	يستدعي، استدعاء
1512	recalled	يستدعي، مستدعى
1513	recalling	يستدعي، استدعاء
1514	recession	انكماش، ركود، كساد
1515	recessionary	ركودي، انكماشي
1516	reckless	طائش، تهور، الإهمال
1517	recklessly	بلا مبالاة
1518	recklessness	التهور، الإهمال
1519	redact	يشطب
1520	redacted	يشطب، مشطوب
1521	redacting	يشطب، مشطوب
1522	redaction	الشطب
1523	redefault	يعيد سداد، إعادة السداد
1524	redefaulted	يعيد سداد
1525	redefaults	يعيد سداد
1526	redress	ينصف، يصحح، يتدارك
1527	redressed	ينصف، يصحح، يتدارك، مصحح
1528	redressing	ينصف، يصحح، يتدارك، التصحيح
1529	refusal	ينكر، يرفض، يمتنع، الأمتناع
1530	refuse	ينكر، يرفض، يمتنع
1531	refused	ينكر، يرفض، يمتنع، مرفوض
1532	refusing	ينكر، يرفض، يمتنع، الأمتناع
1533	reject	يرفض
1534	rejected	يرفض
1535	rejecting	يرفض، مرفوض
1536	rejection	الرفض
1537	relinquish	يتنازل، يتخلى
1538	relinquished	يتنازل، يتخلى
1539	relinquishes	يتنازل، يتخلى
1540	relinquishing	يتنازل، يتخلى
1541	relinquishment	التنازل
1542	reluctance	عزوف، إحجام
1543	reluctant	محجم
1544	renegotiate	يعيد التفاوض
1545	renegotiated	يعيد التفاوض
1546	renegotiates	يعيد التفاوض
1547	renegotiating	يعيد التفاوض، إعادة التفاوض
1548	renegotiation	مفاوضة جديدة، إعادة التفاوض
1549	renounce	يتنازل، يتخلى
1550	renounced	يتنازل، يتخلى
1551	renouncement	التخلي، التنازل
1552	renounces	يتنازل، يتخلى

No.	English Word	Arabic Translation
1553	renouncing	يتنازل، يتخلى
1554	reparation	تعويض
1555	repossessed	يسترد ملكية
1556	repossesses	يسترد ملكية
1557	repossessing	يسترد ملكية
1558	repossession	استرداد ملكية، استرجاع ملكية، استعادة ملكية
1559	repudiate	يتنصل
1560	repudiated	يتنصل
1561	repudiates	يتنصل
1562	repudiating	يتنصل
1563	repudiation	التنصل
1564	resign	يتنحى، يستقيل
1565	resignation	استقالة
1566	resigned	يتنحى، يستقيل
1567	resigning	يتنحى، يستقيل، استقالة
1568	resigns	يتنحى، يستقيل
1569	restate	يعيد التأكيد، يكرر
1570	restated	يعيد التأكيد، يكرر
1571	reassessment	إعادة تقييم، إعادة تقدير
1572	restates	يعيد التأكيد، يكرر
1573	restating	يعيد التأكيد، يكرر، أعاد التأكيد
1574	restructure	يعيد هيكلة، يعيد تنظيم، إعادة تنظيم، إعادة هيكلة
1575	restructured	يعيد هيكلة، يعيد تنظيم
1576	restructures	يعيد هيكلة، يعيد تنظيم
1577	restructuring	يعيد هيكلة، يعيد تنظيم، إعادة تنظيم، إعادة هيكلة
1578	restructurings	يعيد هيكلة، يعيد تنظيم، إعادة تنظيم، إعادة هيكلة
1579	retaliate	ينتقم
1580	retaliated	ينتقم، منتقم
1581	retaliates	ينتقم
1582	retaliating	ينتقم، منتقم
1583	retaliation	الانتقام
1584	retaliatory	انتقامي
1585	retribution	قصاص
1586	revocation	النقض
1587	revoke	ينقض
1588	revoked	ينقض
1589	revoking	ينقض، منقوض، النقض
1590	ridicule	يستهزئ، يسخر
1591	ridiculed	يستهزئ، يسخر
1592	ridiculing	يستهزئ، يسخر، سخرية
1593	riskier	أكثر مخاطرة، أعلى مخاطرة، أكثر خطورة، أعلى خطورة
1594	riskiest	الأكثر مخاطرة، الأعلى مخاطرة، الأكثر خطورة، الأعلى خطورة، الأخطر
1595	risky	خطير، خطر
1596	sabotage	يُخرِّب، يفسد
1597	sacrifice	يضحي
1598	sacrificed	يضحي
1599	sacrificial	فدائي
1600	sacrificing	يضحي
1601	scandals	فضيحة
1602	scandalous	مخزي
1603	scrutinize	تمحيص
1604	scrutinized	يدقق

No.	English Word	Arabic Translation
1605	scrutinizes	يدقق
1606	scrutinizing	يدقق، تمحيص
1607	scrutiny	تمحيص
1608	seize	يحتجز، يصادر
1609	seized	يحتجز، يصادر، محتجز، مصادرة
1610	seizes	يحتجز، يصادر
1611	seizing	يحتجز، يصادر، محتجز، مصادرة
1612	sentenced	محكوم عليه
1613	sentencing	يصدر الحكم، صدور الحكم
1614	serious	جاد، خطير
1615	seriously	بشكل جدي، بشكل خطير، نحو خطير
1616	seriousness	الخطورة
1617	setback	نكسة، انتكاسة
1618	sever	بتر
1619	severe	حاد، قاسي، خطير
1620	severed	مقطوع
1621	severely	بشكل حاد
1622	severity	حِدّة
1623	sharply	بشكل حاد
1624	shocked	مذهول
1625	shortage	شح، عجز
1626	shortfall	العجز
1627	shrinkage	انحسار، التقلص، تضاؤل
1628	shut	يغلق، مغلق
1629	shutdown	إغلاق
1630	shuts	يغلق
1631	shutting	يغلق، إيقاف
1632	slander	يفتري، الافتراء
1633	slandered	يفتري
1634	slanderous	افترائي
1635	slippage	انزلاق
1636	slow	يبطئ، بطيء
1637	slowdown	تراجع
1638	slowed	يبطئ، بطيء
1639	slower	يبطئ
1640	slowest	الأكثر بطء، الأكثر ركودا
1641	slowing	يبطئ
1642	slowly	بشكل بطيء، بنحو بطيء، بصورة بطيئة، بوتيرة بطيئة
1643	slowness	البطء
1644	sluggish	راكد، كسول، بطيء
1645	sluggishly	بشكل بطيء، بنحو بطيء
1646	sluggishness	التثاقل، بطء، الخمول
1647	solvency	الاستقرار المالي، الكفاءة المالية، الملاءة المالية
1648	spam	بريد مزعج، بريد عشوائي
1649	spammers	بريد مزعج، بريد عشوائي
1650	spamming	بريد مزعج، بريد عشوائي
1651	staggering	صادم
1652	stagnant	راكد
1653	stagnate	يركد، ركود
1654	stagnated	يركد، راكد
1655	stagnates	يركد
1656	stagnating	يركد، راكد

No.	English Word	Arabic Translation
1657	stagnation	الركود
1658	standstill	متوقفة
1659	stolen	مسروق
1660	stops	يوقف، التوقف
1661	stoppage	تعطل
1662	stopped	يوقف، متوقف
1663	stopping	يوقف، التوقف
1664	strain	يجهد، إجهاد
1665	strained	يجهد، مجهد
1666	straining	يجهد، إجهاد
1667	stress	يضغط، الضغط
1668	stressed	متوتر
1669	stressful	مقلق، مجهد
1670	stressing	يجهد، إجهاد
1671	stringent	صارم، مشدد
1672	subjected	يخضع، خاضع
1673	subjecting	يخضع، خاضع
1674	subjection	الخضوع
1675	subpoena	يستدعي للمحكمة، أمر قضائي، مذكرة استدعاء، استدعاء قضائي، دعوة للمحكمة
1676	subpoenaed	يستدعي للمحكمة
1677	substandard	دون المستوى، رديء
1678	sue	يقاضي
1679	suffer	يعاني
1680	suffered	يعاني
1681	suffering	يعاني، معاناة
1682	suffers	يعاني
1683	suing	يقاضي، مقاضاة
1684	summoned	أمر قضائي، مذكرة استدعاء، استدعاء قضائي، دعوة للمحكمة، تم استدعائه
1685	summoning	أمر قضائي، مذكرة استدعاء، استدعاء قضائي، دعوة للمحكمة
1686	summons	يجري استدعائه
1687	susceptibility	قابلية
1688	susceptible	سريع التأثر
1689	suspect	يشتبه
1690	suspected	يشتبه، مشتبه به
1691	suspend	يوقف، يعلق
1692	suspended	يوقف، يعلق
1693	suspending	يوقف، يعلق، موقوف، معلق
1694	suspends	يوقف، يعلق
1695	suspension	الإيقاف
1696	suspicion	اشتباه
1697	suspicious	مريب
1698	suspiciously	بشكل مريب، بشكل مثير للريبة
1699	taint	يلطخ
1700	tainted	يلطخ
1701	tainting	يلطخ
1702	tampered	مزور
1703	tense	توتر، متوتر
1704	terminate	يلغي، يفسخ
1705	terminated	يلغي، يفسخ، ملغى
1706	terminates	يلغي، يفسخ
1707	terminating	يلغي، يفسخ
1708	termination	إنهاء

No.	English Word	Arabic Translation
1709	testify	يعترف
1710	testifying	يعترف
1711	threat	يهدد
1712	threaten	يهدد
1713	threatened	يهدد
1714	threatening	يهدد، التهديد
1715	threatens	يهدد
1716	tightening	تشديد
1717	tolerate	يتهاون، يتساهل، يتحمل
1718	tolerated	يتهاون، يتساهل، يتحمل
1719	tolerates	يتهاون، يتساهل، يتحمل
1720	tolerating	يتهاون، يتساهل، يتحمل، متهاون، متساهل
1721	toleration	التحمل
1722	tortuous	شاق، مقعد
1723	tortuously	بشكل معقد، بنحو معقد
1724	tragedy	مأساة، مصيبة
1725	tragic	مأساوي
1726	tragically	بشكل مأساوي
1727	traumatic	مؤلم
1728	trouble	مشاكل، متاعب، مشكلة
1729	troubled	مضطربة
1730	turbulence	تقلبات، اضطراب
1731	turmoil	اضطراب
1732	unable	عاجز، غير قادر، لا يستطيع
1733	unacceptable	مرفوض، مُستهجن
1734	unacceptably	بشكل مرفوض
1735	unaccounted	غير محسوب
1736	unannounced	مفاجئ، غير معلنة
1737	unanticipated	غير متوقع
1738	unapproved	غير مُصرّح به، غير معتمد، غير موافق عليه
1739	unattractive	غير ملفت، غير جذاب
1740	unauthorized	غير مرخصة، غير مصرح به، غير مصرح
1741	unavailability	عدم التوفر
1742	unavailable	غير موجود، غير متاح
1743	unavoidable	لا يمكن تجنبه، حتمي
1744	unavoidably	لا يمكن تجنبه
1745	unaware	يجهل
1746	uncollectable	غير قابل للتحصيل، غير محصل
1747	uncollected	لم يتم تحصيله، غير محصل
1748	uncollectibility	صعوبة التحصيل
1749	uncollectible	غير قابل للتحصيل، لا يمكن تحصيله، مستحيل التحصيل
1750	uncollectibles	غير قابل للتحصيل، لا يمكن تحصيله، مستحيل التحصيل
1751	uncompetitive	غير تنافسي
1752	uncompleted	غير مكتمل
1753	unconscionable	مفرط، جائر، غير معقول
1754	unconscionably	بشكل جائر، بنحو جائر
1755	uncontrollable	خارج السيطره
1756	uncontrolled	غير منضبط
1757	uncorrected	غير معدل، غير مصحح
1758	uncover	يكتشف
1759	uncovered	يكتشف
1760	uncovering	يكتشف

No.	English Word	Arabic Translation
1761	uncovers	يكتشف
1762	undeliverable	مستحيل التسليم، غير قابل للتسليم، لا يمكن تسليمه
1763	undelivered	لم يتم تسليمه، لم يتم تسليمه، غير قابل للتسليم
1764	undercut	يخفض
1765	undercutting	يخفض
1766	underestimate	يقلل من تقدير
1767	underestimated	يقلل من تقدير
1768	underestimating	يقلل من تقدير
1769	underfunded	غير ممول، ضعيف التمويل
1770	undermine	يقوض
1771	undermined	يقوض
1772	undermines	يقوض
1773	undermining	يقوض
1774	underpaid	أجر زهيد
1775	underpayment	سداد منخفض، دفع منخفض
1776	underperform	أداء دون المستوى، غير محقق للطموحات
1777	underperformance	أداء ضعيف، ضعف الأداء
1778	underperformed	أدى دون المستوى، ضعيف الأداء
1779	underperforming	غير محقق للأهداف، أداء دون التوقعات، أداء ضعيف
1780	underperforms	يؤدي دون المستوى
1781	underproduced	ناقص الإنتاج
1782	underproduction	عجز في الإنتاج، إنتاج غير كاف، نقص الإنتاج، قصور الإنتاج
1783	underreporting	عدم الإبلاغ الكامل، قصور في التقارير
1784	understate	يقلل من شأن
1785	understated	يقلل من شأن
1786	understatement	بخس
1787	understates	يقلل من شأن
1788	understating	يقلل من شأن، التخفيف من أهمية
1789	underutilization	قصور في الاستخدام
1790	underutilized	غير مستغل بالكامل، غير قليل الاستخدام
1791	undesirable	غير مرغوب، غير مستحب
1792	undesired	غير مرضي، غير مفضل
1793	undetected	غير مكتشف، لم يتم كشفها، غير مرصود
1794	undetermined	مبهم، غير محدد، غير معلوم
1795	undisclosed	غير معلن، غير مكشوف، غير مفصح عنه، لم يكشف عنها، غير معروف
1796	undocumented	غير موثق
1797	undue	لا داعي له، غير مبرر، غير لازم
1798	unduly	بشكل مفرط، بنحو مفرط
1799	uneconomic	مكلف، ليس مجدي اقتصاديا، غير مجدي اقتصاديا
1800	uneconomical	مكلف، ليس مجدي اقتصاديا، غير مجدي اقتصاديا
1801	uneconomically	بشكل غير اقتصادي
1802	unemployed	عاطل
1803	unemployment	البطالة
1804	unethical	غير أخلاقي، منافي للأخلاق، مناقض للأخلاق، مخالف للأخلاق
1805	unethically	بشكل غير أخلاقي، بنحو غير أخلاقي، بطريقة غير أخلاقية
1806	unexcused	غير مبرر، بدون عذر
1807	unexpected	غير متوقع، مفاجئ، طارئ
1808	unexpectedly	بنحو غير متوقع، بشكل غير متوقع، بصورة غير متوقعة، بشكل مفاجئ، بنحو مفاجئ
1809	unfair	جائرة، مجحف، غير عادل، ليس عادل
1810	unfairly	بشكل غير عادل، بنحو غير عادل، بطريقة غير عادلة
1811	unfavorability	عدم التفضيل
1812	unfavorable	غير مفضل، سلبي

No.	English Word	Arabic Translation
1813	unfavorably	بشكل غير مفضل، بصورة غير مفضلة
1814	unfavourable	غير مفضل
1815	unfeasible	غير ملائم
1816	unfit	غير لائق
1817	unfitness	عدم الملاءمة، عدم الأهلية
1818	unforeseeable	غير قابل للتنبؤ، لا يمكن التنبؤ
1819	unforeseen	مفاجئ، غير مخطط له
1820	unforseen	مفاجئ، غير مخطط له
1821	unfortunate	مؤسف
1822	unfortunately	لسوء الحظ، مع الأسف، للأسف
1823	unfounded	بدون دليل، بلا أساس
1824	unfriendly	غير ودي
1825	unfulfilled	غير مكتمل، غير منجز
1826	unfunded	غير مدعوم مالياً، غير مغطى
1827	uninsured	دون تغطية تأمينية، بلا تأمين، غير مغطى بتأمين، غير مؤمن، بدون تأمين
1828	unintended	غير مقصود، غير متعمد
1829	unintentional	غير مقصود، غير متعمد، غير مخطط له، دون قصد
1830	unintentionally	بشكل غير متعمد، عن غير قصد، بشكل غير مقصود
1831	unjust	ظالم
1832	unjustifiable	غير مبرر، غير مبررة، غير قابل للتبرير
1833	unjustifiably	بدون سبب، بشكل غير مبرر، بطريقة غير مقبولة
1834	unjustified	غير مبرر، دون مبرر، بلا مبرر
1835	unjustly	بشكل غير عادل، بدون وجه حق، بشكل مجحف، بشكل غير منصف
1836	unknowing	دون إدراك، بدون علم، دون معرفة
1837	unknowingly	بدون معرفة، بدون دراية، دون إدراك
1838	unlawful	غير قانوني، مخالف للقانون، منافي للقانون
1839	unlawfully	بشكل غير قانوني، بطريقة غير قانونية، بشكل مخالف للقانون
1840	unlicensed	غير مرخص، دون ترخيص، بدون رخصة
1841	unliquidated	غير مصفى
1842	unmarketable	غير رائج
1843	unmerchantable	غير جيد للتجارة، غير قابل للتجارة، غير قابل للتسويق، غير صالح للبيع
1844	unmeritorious	غير جدير بالتقدير
1845	unnecessarily	لا داعي له، بشكل غير ضروري، بلا داع
1846	unnecessary	لا داعي له، غير ضروري
1847	unneeded	غير لازم
1848	unobtainable	غير قابل للحصول، بعيد المنال
1849	unoccupied	شاغر، غير مأهول
1850	unpaid	غير مدفوع
1851	unperformed	غير منجز
1852	unplanned	غير متوقع، بدون تخطيط
1853	unpopular	غير رائج
1854	unpredictability	لا يُمكن التنبؤ
1855	unpredictable	متقلب، لا يمكن التنبؤ، غير قابل للتنبؤ
1856	unpredictably	بشكل متقلب، بصورة متقلبة
1857	unpredicted	غير متوقع، غير متنبئ به
1858	unproductive	غير منتج، غير مثمر
1859	unprofitability	انعدام الجدوى المالية
1860	unprofitable	غير مربح، غير مجدي مالياً
1861	unqualified	غير كفؤ، غير مؤهل
1862	unrealistic	غير واقعي
1863	unreasonable	غير معقول، غير منطقي
1864	unreasonableness	عدم المعقولية

No.	English Word	Arabic Translation
1865	unreasonably	بشكل غير معقول، بشكل غير منصف، بشكل غير منطقي
1866	unreceptive	غير مستجيب
1867	unrecoverable	لا يمكن استعادته، غير قابل للاسترداد، لا يمكن استرداده
1868	unrecovered	غير قابل للاسترداد
1869	unreimbursed	بدون تعويض، بلا تعويض
1870	unreliable	غير موثوق
1871	unremedied	غير معالج، غير مصحح
1872	unreported	غير مبلغ عنه
1873	unresolved	غير محلول
1874	unrest	اضطراب
1875	unsafe	خطر، غير آمن
1876	unsalable	غير قابل للبيع
1877	unsaleable	غير قابل للبيع
1878	unsatisfactory	غير مرضي
1879	unsatisfied	غير راضٍ
1880	unsavory	منفر
1881	unscheduled	غير مجدول
1882	unsellable	غير قابل للبيع
1883	unsold	غير مباع
1884	unsound	غير متين
1885	unstabilized	غير مستقر
1886	unstable	غير مستقر
1887	unsubstantiated	غير مؤكد
1888	unsuccessful	فاشل، غير ناجح
1889	unsuccessfully	بشكل فاشل، بشكل غير ناجح، بنحو غير ناجح
1890	unsuitability	عدم الانسجام
1891	unsuitable	غير ملائم، غير مناسب
1892	unsuitably	بشكل غير ملائم، بنحو غير ملائم
1893	unsuited	غير مطابق
1894	unsure	متردد، غير واثق
1895	unsuspected	غير متوقع
1896	unsuspecting	غير مدرك، غير واعي
1897	unsustainable	غير مستدام
1898	untenable	غير منطقي
1899	untimely	في غير وقته، قبل الأوان
1900	untrusted	غير مأمون
1901	untruth	كذب
1902	untruthful	غير أمين
1903	untruthfully	بشكل غير موثوق، بشكل غير صادق، بشكل كاذب
1904	untruthfulness	الكذب
1905	unusable	غير صالح للإستعمال، غير صالح للاستخدام، غير قابل للاستخدام
1906	unwanted	غير مرغوب، غير مرحب به
1907	unwarranted	غير مبرر
1908	unwelcome	غير مرحب به
1909	unwilling	عدم الرغبة
1910	unwillingness	عزوف
1911	upset	مستاء
1912	urgency	الالحاح
1913	urgent	ملح
1914	usurious	مرابي
1915	usurp	ينتزع، يغتصب
1916	usurped	ينتزع، يغتصب، منتزع

No.	English Word	Arabic Translation
1917	usurping	ينتزع، يغتصب، الانتزاع، الاستيلاء
1918	usurps	ينتزع، يغتصب
1919	usury	انتهازية مالية، استغلال مالي
1920	vandalism	عبث، تخريب
1921	verdict	صدور حكم
1922	vetoed	نقض، منقوض
1923	victims	ضحية
1924	violate	ينتهك
1925	violated	ينتهك، منتهك
1926	violates	ينتهك
1927	violating	ينتهك، منتهك
1928	violation	انتهاك
1929	violative	منتهك
1930	violator	منتهك
1931	violence	شدة، عنف
1932	violent	عنيف
1933	violently	بشكل عنيف، بنحو عنيف
1934	vitiate	يفسد
1935	vitiated	يفسد، مفسد
1936	vitiates	يفسد
1937	vitiating	يفسد
1938	vitiation	إفساد
1939	voided	باطل
1940	voiding	يبطل
1941	volatile	متقلب، غير مستقر
1942	volatility	تقلب، تذبذب
1943	vulnerability	عالي التأثر
1944	vulnerable	هش
1945	vulnerably	بشكل هش
1946	warn	يحذر، ينذر
1947	warned	يحذر، ينذر
1948	warning	يحذر، ينذر
1949	warns	يحذر، ينذر
1950	wasted	ضائع، مهدرة
1951	wasteful	ضائع
1952	wasting	ضائع
1953	weak	يضعف، ضعيف، هزيل
1954	weaken	يضعف
1955	weakened	يضعف، ضعيف، هزيل
1956	weakening	يضعف، ضعيف، هزيل
1957	weakens	يضعف
1958	weaker	أضعف
1959	weakest	الأكثر ضعف
1960	weakly	بشكل ضعيف، بنحو ضعيف
1961	weakness	الضعف
1962	willfully	بشكل متعمد
1963	worry	القلق، خوف
1964	worrying	القلق
1965	worse	أسوأ
1966	worsen	يتفاقم
1967	worsened	يتفاقم
1968	worsening	يتفاقم، متدهور

No.	English Word	Arabic Translation
1969	worsens	يتفاقم
1970	worst	الأكثر سوءا
1971	worthless	لا قيمة له، بلا قيمة
1972	writedown	يهلك، إهلاك
1973	writedowns	يهلك
1974	writeoff	شطب دين
1975	writeoffs	شطب دين
1976	wrong	مخطئ، خاطئ، نحو خاطئ، بشكل خاطئ
1977	wrongdoing	مخالفة، مخطئ، خاطئ
1978	wrongful	مخطئ، خاطئ، جائر
1979	wrongfully	بشكل خاطئ، بنحو خاطئ، بشكل غير عادل، بنحو غير عادل
1980	wrongly	بشكل خاطئ، بنحو خاطئ

Table A2. (b-2) Negative English to Lemmatized Arabic Translation (*N=5,773*)

No.	English Word	Arabic Translation
1	abandon	تَرَك، هَجَر، تَخَلَّى، تَنازَل
2	abandoned	مَتْرُوك، تَرَك، تَنازُل، مَهْجُور، مُهْمَل، هَجَر، تَخَلَّى
3	abandoning	تَخَلِّي، تَخَلَّى، تَنازُل، تَنازَل، هَجْر، هَجَر
4	abandonment	تَرْك، تَخَلِّي، إعْراض، هَجْر
5	abdicated	تَنازُل، تَخَلَّى، تَنَحَّى، مَتْرُوك، اِعْتَزَل
6	abdicates	اِعْتَزَل، تَنَحَّى، تَنازَل، تَخَلَّى
7	abdicating	اِعْتَزَل، تَنَحَّى، تَنازَل، تَخَلَّى، تَنازُل، تَخَلِّي، اِعْتِزال
8	abdication	تَنازُل، تَخَلِّي، اِعْتِزال
9	aberrant	شاذّ، غَيْر طَبِيعِيّ، مُضْطَرِب، مُنْحَرِف
10	aberration	اِنْحِراف، شَذّ، اِضْطِراب
11	aberrational	غَيْر اِعْتِياد، غَيْر طَبِيعِيّ، مُضْطَرِب، شاذّ
12	abetting	تَحْرِيض، حَرَّض
13	abnormal	غَيْر طَبِيعِيّ، غَيْر عادِيّ، شاذّ
14	abnormality	اِخْتِلال، اِضْطِراب
15	abnormally	شَكْل شاذّ، صُورَة شاذّ، نَحْو شاذّ، طَرِيقَة شاذّ، شَكْل غَيْر طَبِيعِيّ، صُورَة غَيْر طَبِيعِيّ، نَحْو غَيْر طَبِيعِيّ، طَرِيقَة غَيْر طَبِيعِيّ
16	abolish	أَلْغَى، أزال، بَطَل، مَحا، إِلْغاء، إِبْطال، إزالَة
17	abolished	أَلْغَى، أزال، بَطَل، مَحا، مُلْغَى
18	abolishes	أَلْغَى، أزال، بَطَل، مَحا
19	abolishing	أَلْغَى، أزال، بَطَل، مَحا، إِلْغاء، إِبْطال، إزالَة
20	abrogate	أَلْغَى، فَسَخ، بَطَل، نَقَض
21	abrogated	أَلْغَى، فَسْخ، بَطَل، نَقْض، مُلْغَى، مُبْطَل
22	abrogates	أَلْغَى، فَسَخ، بَطَل، نَقَض، أَسْقَط
23	abrogating	أَلْغَى، فَسَخ، بَطَل، نَقَض، أَسْقَط
24	abrogation	إِلْغاء، إِبْطال، نَقْض
25	abrupt	مُفاجِئ، حادّ، مُباغِت، فَظّ
26	abruptly	صُورَة مُفاجِئ، شَكْل مُفاجِئ، نَحْو مُفاجِئ، طَرِيقَة مُفاجِئ، صُورَة مُباغِت، شَكْل مُباغِت، نَحْو مُباغِت، طَرِيقَة مُباغِت، صُورَة حادّ، شَكْل حادّ، نَحْو حادّ، طَرِيقَة حادّ
27	abruptness	حِدَّة
28	absence	فِقْدان، اِنْعِدام، غِياب، اِفْتِقار
29	absenteeism	تَغَيُّب
30	abuse	أساء، اِنْتَهَك، اِعْتَدَى، إساءَة، اِنْتِهاك، تَعَدِّي
31	abused	أساء، اِنْتَهَك، اِعْتَدَى
32	abusing	أساء، اِنْتَهَك، اِعْتَدَى، إساءَة، اِنْتِهاك، تَعَدِّي
33	abusive	تَعَسُّفِيّ، مُؤْذِي
34	abusively	شَكْل تَعَسُّفِيّ، نَحْو تَعَسُّفِيّ، شَكْل مُسِيء، نَحْو مُسِيء، صُورَة مُسِيء، طَرِيقَة مُسِيء
35	abusiveness	سُوء مُعامَلَة، إساءَة
36	accident	حادِث، واقِعَة
37	accidental	غَيْر مَقْصُود، غَيْر مُتَعَمَّد
38	accidentally	طَرِيق خَطَأ، دُون قَصَد، غَيْر مُتَعَمَّد، سَهْو
39	accusation	اِتِّهام، تُهْمَة، اِدِّعاء
40	accuse	لام، اِتَّهَم، اِدَّعَى
41	accused	اِتَّهَم، مُتَّهَم، مَلام
42	accuses	لام، اِتَّهَم، شَكَّك، اِدَّعَى
43	accusing	لام، اِتَّهَم، شَكَّك، اِدَّعَى، لَوْم، اِدِّعاء
44	acquiesce	إِذْعان، رُضُوخ، ذَعِن، رَضَخ
45	acquiesced	رَضَخ، أَذْعَن
46	acquiesces	ذَعِن، رَضَخ
47	acquiescing	إِذْعان، رُضُوخ
48	acquit	أَعْفَى، بَرَّأ

No.	English Word	Arabic Translation
49	acquits	أعْفَى، بَرَّأ
50	acquittal	مُخالَصَة، تَبْرِئَة، بَراءَة، إِبْراء
51	acquitted	بَرَّأ، تَمّ تَبْرِئَة، صَدَر بَراءَة
52	acquitting	إِصْدار بَراءَة، إِعْلان بَراءَة، تَبْرِئَة، إِزالَة تُهْمَة، أعْفَى، بَرَّأ
53	adulterate	غَشّ، زَيَّف، مُزَيَّف، مَغْشُوش
54	adulterated	غِشّ، زَيْف، مُزَيَّف، مَغْشُوش
55	adulterating	غَشّ، زَيَّف، تَزْيِيف، غِشّ
56	adulteration	غِشّ، تَزْيِيف
57	adversarial	مُعارِض، مُناوِئ، مُناهِض، عَدّاء، خُصُومَة
58	adversary	مُناوِئ، مُناهِض، عَدُوّ، مُنافِس
59	adverse	ضارّ، مُناوِئ، مُناهِض، سَلْبِيّ، مُعاكِس، مُضادّ، عاجِز
60	adversely	شَكْل سَلْبِيّ، صُورَة سَلْبِيّ، نَحْو سَلْبِيّ، طَرِيقَة سَلْبِيّ، شَكْل ضارّ، نَحْو ضارّ، صُورَة ضارّ، طَرِيقَة ضارّ، شَكْل مُعاكِس، نَحْو مُعاكِس، صُورَة مُعاكِس، طَرِيقَة مُعاكِس
61	adversity	مُصِيبَة، أزْمَة، شِدَّة، مِحْنَة، نَكْسَة
62	aftermath	عاقِبَة
63	against	ضِدّ، عَكْس
64	aggravate	أثار، صَعَّب، أزَّم
65	aggravated	أثار، صَعَّب، أزَّم، جَسِيم، مُتَفاقِم
66	aggravates	أثار، صَعَّب، أزَّم
67	aggravating	أثار، صَعَّب، أزَّم، جَسِيم، مُتَفاقِم
68	aggravation	إِثارَة، صُعُوبَة، مُحَذِّر
69	alerted	نَبَّه، أنْذَر، مُتَأهِّب، حَذَّر
70	alerting	إِنْذار، تَحْذِير، نَبَّه، تَنْبِيه، اِسْتِنْفار، تَمّ خَطَر
71	alienate	بَعُد، نَفَر، عَزَل، نَبَذ، نَقَل مِلْكِيَّة
72	alienated	بَعُد، نَفَر، عَزَل، نَبَذ، نَقَل مِلْكِيَّة، مَنْبُوذ، مُسْتَبْعَد، مَعْزُول
73	alienates	بَعُد، نَفَر، عَزَل، نَبَذ، نَقَل مِلْكِيَّة
74	alienating	بَعُد، نَفَر، عَزَل، نَبَذ، مَنْبُوذ، مُسْتَبْعَد، مَعْزُول
75	alienation	عُزْلَة، إِبْعاد، نَقْل مِلْكِيَّة، نَفْرَة
76	allegation	اِتِّهام، مَزْعَمَة، اِفْتِراء
77	allege	زَعَم، اِحْتاج، تَذَرَّع، اِتَّهَم، اِدَّعَى
78	alleged	زَعَم، اِحْتاج، تَذَرَّع، اِتَّهَم، اِدَّعَى، مَزْعُوم، اِدِّعاء، مَدْعاة
79	allegedly	زَعَم أنَّ، كَما زَعَم، حَسَب اِدِّعاء
80	alleges	زَعَم، اِحْتاج، تَذَرَّع، اِتَّهَم، اِدَّعَى
81	alleging	زَعَم، اِحْتاج، تَذَرَّع، اِتَّهَم، اِدَّعَى، مَزْعُوم، اِدِّعاء، مَدْعاة
82	annoy	ضايَق، أزْعَج، اِنْزَعَج، أغْضَب، اِسْتَفَزّ
83	annoyance	اِنْزِعاج، إِزْعاج، اِسْتِياء، مُضايَقَة
84	annoyed	ضايَق، أزْعَج، اِنْزَعَج، أذَى، مُتَضايِق، مُزْعِج، مُنْزَعِج، غاضِب
85	annoying	،ضايَق، أزْعَج، اِنْزَعَج، مُتَضايِق، مُزْعِج، مُنْزَعِج، غاضِب، اِنْزِعاج، إِزْعاج، تَضايَق مُضايَقَة
86	annoys	ضايَق، أزْعَج، اِنْزَعَج، أغْضَب، اِسْتَفَزّ، آذَى
87	annul	ألْغَى، بَطَّل، فَسَخ
88	annulled	ألْغَى، بَطَّل، فَسَخ، مُلْغَى، مُبْطَل، مَوْقُوف
89	annulling	ألْغَى، بَطَّل، فَسَخ، إِبْطال
90	annulment	إِلْغاء، بَطَّل، تَعْطِيل
91	annuls	ألْغَى، بَطَّل، فَسَخ
92	anomalous	شاذّ، غَيْر عادِيّ، غَرِيب، مُنْحَرِف، غَيْر طَبِيعِيّ
93	anomalously	،شَكْل غَيْر طَبِيعِيّ، صُورَة غَيْر طَبِيعِيّ، شَكْل غَيْر طَبِيعِيّ، نَحْو غَيْر طَبِيعِيّ، نَحْو شاذّ شَكْل شاذّ، صُورَة شاذّ، طَرِيقَة شاذّ
94	anomaly	شَذّ، اِنْحِراف، اِخْتِلال
95	anticompetitive	مُخالِف رُوح مُنافَسَة، مُناهِض تَنافُس، مُضادّ مُنافَسَة، ضِدّ مُنافَسَة، ضِدّ مُنافَسَة
96	antitrust	ضِدّ اِحْتِكار، مُحارَبَة اِحْتِكار، مُناهِض اِحْتِكار، مُضادّ اِحْتِكار، مُكافَحَة اِحْتِكار
97	argue	اِحْتاج، تَجادَل، جادَل، دافَع، بَرَّر

No.	English Word	Arabic Translation
98	argued	اِحْتاج، تَجادَل، جادَل، دافَع، بَرَّر
99	arguing	اِحْتاج، تَجادَل، جادَل، دافَع، بَرَّر، جِدال
100	argument	نِزاع، جِدال، خِلاف، حُجَّة
101	argumentative	خِلاف، جَدَل، مَحَلّ خِلاف، مَحَلّ جَدَل، مَحَلّ نِزاع
102	arrearage	مُتَأَخِّر، تَخَلّف عَن سَداد، تَأَخُّر عَن سَداد
103	arrearages	مُتَأَخِّرات، تَخَلّف عَن سَداد، تَأَخُّر عَن سَداد
104	arrears	مُسْتَحِقّ غَيْر مَدْفُوع، قِسْط مُتَأَخِّر، مُتَأَخِّرات، تَأْخِير فِي دَفْع، دَيْن مُعَلّق
105	arrest	اِعْتَقَل، اِعْتِقال، اِحْتَجَز
106	arrested	اِعْتَقَل، مُحْتَجَز، مَحْبُوس
107	artificially	نَحْو مُصْطَنَع، صُورَة اِصْطِناعِيّ، شَكْل مُصْطَنَع
108	assault	تَعَدَّى، تَهَجَّم، هاجَم، تَعَدِّي، تَهَجُّم، اِعْتِداء
109	assaulted	اِعْتَدَى، هَجَم، هاجَم، مُتَعَدِّي عَلَى، تَعَرَّض اِعْتِداء، تَمّ هُجُوم عَلَى
110	assaulting	تَعَدَّى، تَهَجَّم، هاجَم، تَعَدِّي، تَهَجُّم، اِعْتِداء
111	assertions	اِدِّعاء
112	attrition	اِسْتِنْزاف، تَناقُص، تَآكُل، اِنْكِماش
113	aversely	طَرِيقَة عَكْسِيّ، شَكْل عَكْسِيّ، نَحْو عَكْسِيّ، صُورَة عَكْسِيّ، شَكْل سَلْبِيّ، نَحْو سَلْبِيّ، صُورَة سَلْبِيّ، طَرِيقَة سَلْبِيّ
114	backdating	تارِيخ رَجْعِيّ، تارِيخ مُسْبَق
115	bad	سَيِّء، رَدِيء، سُوء، غَيْر صالِح
116	bail	كَفَل، إِنْقاذ، كَفالَة، إِفْراج
117	bailout	إِنْقاذ، إِغاثَة مالِيّ، دَعْم مالِيّ طارِئ، إِسْعاف
118	balk	صَدّ، أَعاق، تَرَدَّد، عائِق
119	balked	صَدّ، أَعاق، تَرَدَّد، تَحَفَّظ
120	bans	حَظَر، مَنَع
121	bankrupt	فَلّس، مُفْلِس، إِفْلاس، مُعْسِر، مَدْيُون
122	bankruptcy	إِفْلاس، إِعْسار
123	bankrupted	أَفْلَس، مُفْلِس، مُعْسِر، مَدْيُون
124	bankrupting	فَلّس، مُفْلِس، إِفْلاس، إِعْسار، مُعْسِر
125	barred	حَظَر، مَنَع، حَجَب، مَحْجُوب، مَحْظُور، مَمْنُوع، مَسْدُود، مَوْقُوف
126	barrier	سُدّ، عائِق، حاجِز
127	bottleneck	أَعاق، مَأْزِق، عائِق، خانِق
128	boycott	قاطَع، مُقاطَعَة
129	boycotted	تَمّ حَظْر، تَمّ مُقاطَعَة، قاطَع
130	boycotting	قاطَع، مُقاطَعَة
131	breach	خَرَق، نَقَض، اِنْتَهَك، خَرْق، مُخالِف، صَدْع، ثُغْرَة، إِخْلال، اِنْتِهاك، اِخْتِراق، فَجْوَة
132	breached	خَرَق، نَقَض، اِنْتَهَك، مُخْتَرَق، مُنْتَهَك
133	breaching	خَرَق، نَقَض، اِنْتَهَك، مُخْتَرَق، مُنْتَهَك
134	break	اِقْتَحَم، اِنْتَهَك، كَسَر، خَرَق، اِنْهار
135	breakages	تَلَف، كَسْر، عَجْز
136	breakdown	اِنْهِيار، اِنْقِطاع، عَطَّل، فَشَل، عَطَل
137	bribe	رَشا، رَشْوَة
138	bribed	رَشا، رَشْوَة
139	bribery	رَشْوَة
140	bribing	رَشا، رَشْوَة
141	burden	أَثْقَل، أَرْهَق، حَمَل، عِبْء
142	burdened	أَثْقَل، أَرْهَق، مُثْقَل، مَحْمَل
143	burdening	أَثْقَل، أَرْهَق، مُثْقَل، مُرْهِق، حَمْل، عِبْء
144	burdensome	مُرْهِق، ثَقِيل، قاسِي
145	burned	أَحْرَق، إِحْراق
146	calamitous	مُدَمِّر، كارِثِي، فاجِع، مَأْسَوِيّ
147	calamity	مُصِيبَة، أَزْمَة، كارِثَة، فاجِع، مِحْنَة
148	cancel	حَذَف، أَلْغَى، شَطَب

No.	English Word	Arabic Translation
149	canceled	حَذَف، أَلْغَى، مَشْطُوبٌ، مُلْغَى، مُبْطَل، تَمّ إِلْغاء
150	canceling	حَذَف، أَلْغَى، شَطَب، مَشْطُوبٌ، مُلْغَى، مُبْطَل
151	cancellation	إِلْغاء، شَطْب
152	cancelled	حَذَف، أَلْغَى، مَشْطُوبٌ، مُلْغَى، مُبْطَل، تَمّ إِلْغاء
153	cancelling	حَذَف، أَلْغَى، شَطَب، مَشْطُوبٌ، مُلْغَى، مُبْطَل
154	careless	مُهْمَل، مُتَساهِل، مُسْتَهْتَر، مُتَهَوِّر، طائِش، غَيْر مُبالِي
155	carelessly	شَكْل مُتَهَوِّر، صُورَة مُتَهَوِّر، طَرِيقَة مُتَهَوِّر، نَحْو مُتَهَوِّر، شَكْل غَيْر مُبالِي، نَحْو غَيْر مُبالِي
156	carelessness	لامُبالاة، إِهْمال، تَهَوُّر
157	catastrophe	مُصِيبَة، أَزْمَة، فاجِع، كارِثَة، مِحْنَة
158	catastrophic	مَأسَوِيّ، مُدَمِّر، فاجِع، كارِثي، وَخِيم
159	catastrophically	نَحْو مَأسَوِيّ، شَكْل كارِثي، نَحْو كارِثي، شَكْل مَأسَوِيّ
160	caution	حِيطَة، اِحْتِراس، تَرَوِّي، حِذْر
161	cautionary	وِقائِيّ، تَحْذِير، اِحْتِراز
162	cautioned	أَنْذَر، نَبَّه، حَذَّر
163	cautioning	أَنْذَر، نَبَّه، حَذَّر، اِحْتِراس، تَحْذِير، إِنْذار
164	cease	وَقَّف، قَطَع، أَنْهَى، تَوَقُّف، اِمْتِناع
165	ceased	تَوَقَّف، قَطَع، أَنْهَى، مَوْقِف
166	ceasing	تَوَقُّف، إِنْهاء، إِيقاف، اِمْتِناع
167	censure	وَبَّخ، اِسْتَهْجَن، اِنْتَقَد، لام، اِسْتَنْكَر، اِسْتِنْكار، اِنْتِقاد، تَوْبِيخ، اِسْتِهْجان، لَوْم
168	censured	وَبَّخ، اِسْتَهْجَن، اِنْتَقَد، لام، اِسْتَنْكَر
169	censuring	وَبَّخ، اِسْتَهْجَن، اِنْتَقَد، لام، اِسْتَنْكَر، اِسْتِنْكار، اِنْتِقاد، تَوْبِيخ، اِسْتِهْجان، لَوْم
170	challenge	تَحَدَّى، اِعْتَرَض، تَحَدِّي
171	challenged	تَحَدَّى، اِعْتَرَض، تَحَدِّي
172	challenging	تَحَدِّي، مُعَقَّد، صَعْب
173	chargeoffs	دَيْن مَعْدُوم، خَصْم دَيْن، شَطْب مَبْلَغ مَدِينَة
174	circumvent	تَفادَى، تَجَنَّب، راوَغ، تَهَرَّب
175	circumvented	تَفادَى، تَجَنَّب، راوَغ
176	circumventing	تَفادَى، تَجَنَّب، راوَغ، مُراوَغَة، تَحايُل، اِلْتِفاف
177	circumvention	تَحايُل
178	circumvents	تَفادَى، تَجَنَّب، راوَغ، تَهَرَّب
179	claims	طالَب، اِدَّعَى، مُطالَبَة، اِدِّعاء
180	claiming	طالَب، اِدَّعَى، مُطالَبَة، اِدِّعاء
181	clawback	اِسْتِرْداد مال، اِسْتِرْداد مَدْفُوع، اِسْتِرْجاع مَبْلَغ، اِسْتِعادَة مال
182	closeout	تَصْفِيَة، إِغْلاق
183	closings	أَنْهَى، أَقْفَل، أَغْلَق، صَفَّى، تَصْفِيَة، إِغْلاق، إِقْفال
184	closure	إِغْلاق، إِقْفال، إِنْهاء
185	coerce	أَجْبَر، كَرِه، أَرْغَم، اِضْطَرّ
186	coerced	أَجْبَر، كَرِه، أَرْغَم، اِضْطَرّ، مُجْبَر
187	coerces	أَجْبَر، كَرِه، أَرْغَم
188	coercing	أَجْبَر، كَرِه، أَرْغَم، إِجْبار، إِكْراه
189	coercion	إِجْبار، إِكْراه، قَسْر
190	coercive	قَهْر، إِكْراه، إِجْبار، قَسْرِيّ، قَمْع
191	collapse	خَفَق، اِنْهار، تَهاوَى، أَسْقَط، اِنْهِيار، سُقُوط، تَهاوَى
192	collapsed	خَفَق، اِنْهار، تَهاوَى، أَسْقَط، مُنْهار
193	collapsing	خَفَق، اِنْهار، تَهاوَى، أَسْقَط، اِنْهِيار، إِخْفاق، مُنْهار
194	collision	تَضارُب، تَصادُم، اِصْطِدام
195	collude	تَواطَأ، تَآمَر
196	colluded	تَواطَأ، تَآمَر
197	colludes	تَواطَأ، تَآمَر
198	colluding	تَواطَأ، تَآمَر، مُتَواطِئٌ، تَواطُؤ، تَآمُر
199	collusion	تَواطُؤ، تَآمُر، مُؤامَرَة

No.	English Word	Arabic Translation
200	collusive	مُتَوَاطِئٌ، مُتَآمِر
201	complain	تَذَمَّر، شَكا، اِنْتَقَد، اِشْتَكَى، شَكْوَى، تَذَمُّر
202	complained	تَذَمَّر، شَكا، اِنْتَقَد، اِشْتَكَى
203	complaining	تَذَمَّر، شَكا، اِنْتَقَد، اِشْتَكَى، شَكْوَى، تَذَمُّر
204	complains	تَذَمَّر، شَكا، اِنْتَقَد، اِشْتَكَى
205	complaint	تَذَمُّر، شَكْوَى، لَوْم، اِعْتِراض
206	complicate	صَعُب
207	complicated	صَعُب، مُعَقَّد
208	complicates	صَعُب
209	complicating	صَعُب، تَعْقِيد
210	complication	تَعْقِيد، صُعُوبَة، إِشْكالِيّ
211	compulsion	إِلْحاح، إِجْبار، إِلْزام، إِكْراه، قَسَر
212	concealed	كَتَّم، أَخْفَى، حَجَب، مَخْفِيّ، مُخَبَّأَة، سَرِي
213	concealing	كَتَّم، أَخْفَى، حَجَب، مَخْفِيّ، مُخَبَّأَة، سَرِي
214	concede	تَنازَل، سَلَّم، قَبِل، اِعْتَرَف، رَضَخ، ذَعِن
215	conceded	تَنازَل، سَلَّم، قَبِل، اِعْتَرَف، رَضَخ، ذَعِن
216	concedes	تَنازَل، سَلَّم، قَبِل، اِعْتَرَف، رَضَخ، ذَعِن
217	conceding	تَنازَل، سَلَّم، قَبِل، اِعْتَرَف، رَضَخ، ذَعِن، تَنازُل، اِسْتِسْلام، إِذْعان
218	concern	أَقْلَق، قَلَق، اِكْتِراث
219	concerned	أَقْلَق، مُقْلِق
220	conciliating	صالَح، مُصالَحَة، تَسْوِيَة، تَهْدِئَة، اِسْتِرْضاء
221	conciliation	مُصالَحَة، تَسْوِيَة، تَهْدِئَة، اِسْتِرْضاء
222	condemn	شَجَب، اِسْتَهْجَن، أَدان، اِسْتَنْكَر، شَجَب، وَبَّخ، جَرَّم، نَدَّد
223	condemnation	شَجَب، اِسْتِهْجان، تَنْدِيد، تَوْبِيخ، تَجْرِيم
224	condemned	شَجَب، اِسْتَهْجَن، أَدان، اِسْتَنْكَر، شَجَب، وَبَّخ، جَرَّم، نَدَّد، مُدان
225	condemning	شَجَب، اِسْتَهْجَن، أَدان، اِسْتَنْكَر، شَجَب، وَبَّخ، جَرَّم، نَدَّد، مُدان، شَجَب، اِسْتِهْجان، تَنْدِيد، تَوْبِيخ، تَجْرِيم
226	condemns	شَجَب، اِسْتَهْجَن، أَدان، اِسْتَنْكَر، شَجَب، وَبَّخ، جَرَّم، نَدَّد
227	condone	تَنازَل، تَغاضَى، غَفَر
228	condoned	تَنازَل، تَغاضَى، غَفَر
229	confess	اِعْتَرَف
230	confessed	اِعْتَرَف، مُعْتَرَف
231	confesses	اِعْتَرَف
232	confessing	اِعْتَرَف، اِعْتِراف
233	confession	اِعْتِراف
234	confined	قَيَّد، اِحْتَجَز، حَبَس، عَزَل، مَحْصُور، مُقَيَّد، مُحْتَجَز، مَعْزُول
235	confinement	حَجْز
236	confines	حَصَر، قَيَّد، اِحْتَجَز، حَبَس
237	confining	حَصَر، قَيَّد، اِحْتَجَز، حَبَس، مَحْصُور، مُقَيَّد، مُحْتَجَز، مَعْزُول
238	confiscate	اِنْتَزَع، صادَر، اِسْتَوْلَى، حَجَز
239	confiscated	اِنْتَزَع، صادَر، اِسْتَوْلَى، حَجَز، مَصادَر
240	confiscates	اِنْتَزَع، صادَر، اِسْتَوْلَى، حَجَز
241	confiscating	اِنْتَزَع، صادَر، اِسْتَوْلَى، حَجَز
242	confiscation	اِنْتِزاع، مُصادَر، اِحْتِجاز، نَزْع مِلْكِيَّة
243	conflict	تَضارَب، تَناقَض، تَعارَض، خِلاف، نِزاع، صِراع، تَعارُض، تَضارُب
244	conflicted	تَضارَب، تَناقَض، تَعارَض، مُتَضارِب، مُتَناقِض، مُتَعارِض
245	conflicting	تَضارَب، تَناقَض، تَعارَض، مُتَضارِب، مُتَناقِض، مُتَعارِض، خِلاف، نِزاع، صِراع، تَعارُض، تَضارُب
246	confront	جابَه، تَصَدَّى
247	confrontation	مُواجَهَة، مُجابَهَة، نِزاع
248	confrontational	عَدّاء، اِسْتِفْزاز، تَصادُم، جَدّال
249	confronted	جابَه، تَصَدَّى

No.	English Word	Arabic Translation
250	confronting	جابَه، تَصَدَّى، مُواجَهَة، مُجابَهَة، نِزاع
251	confronts	جابَه، تَصَدَّى
252	confuse	ضَلّل، أرْبَك، شَوَّش، خَلَط
253	confused	ضَلّل، أرْبَك، شَوَّش، مَشُوش
254	confuses	ضَلّل، أرْبَك، شَوَّش
255	confusing	مُحَيِّر، مُرْبِك، أرْبَك، مُلْتَبِس، إرْباك، مَشُوش، شَوَّش، تَشْوِيش
256	confusingly	طَرِيقَة مُرْبِك، صُورَة مُرْبِك، شَكْل مُرْبِك، نَحْو مُرْبِك، شَكْل مُحَيِّر، صُورَة مُحَيِّر، طَرِيقَة مُحَيِّر، نَحْو مُحَيِّر
257	confusion	اِرْتِباك، إرْباك، تَداخُل
258	conspiracy	مُؤامَرَة، مَكِيدَة، تَآمُر
259	conspirator	مُتَآمِر، مُتَوَاطِئٌ
260	conspiratorial	تَآمُر، تَواطُؤ
261	conspire	تَآمَر، كاد، تَواطَأ
262	conspired	تَآمَر، كاد، تَواطَأ، مُتَآمِر، مُتَوَاطِئٌ
263	conspires	تَآمَر، كاد، تَواطَأ
264	conspiring	تَآمَر، كاد، تَواطَأ، مُتَآمِر، مُتَوَاطِئٌ، مُؤامَرَة، مَكِيدَة، تَآمُر
265	contempt	اِزْدِراء، سُخْرِيَّة، اِسْتِخْفاف، اِحْتِقار
266	contend	جادَل، كافَح، ناضَل، نافَس
267	contended	جادَل، كافَح، ناضَل، نافَس
268	contending	جادَل، كافَح، ناضَل، نافَس
269	contends	جادَل، كافَح، ناضَل، نافَس
270	contention	جِدال، خِلاف، تَنازُع، صِراع، نِزاع
271	contentious	مُثِير جَدَل، مَوْضِع خِلاف، خِلاف، شائِك، مُتَنازَع عَلَى، مُثِير نِزاع
272	contentiously	شَكْل مُثِير جَدَل، نَحْو مُثِير جَدَل، صُورَة مُثِير جَدَل، طَرِيقَة مُثِير جَدَل، شَكْل جَدَل، صُورَة جَدَل، نَحْو جَدَل، طَرِيقَة جَدَل
273	contested	صارَع، نازَع، مَوْضِع خِلاف، مُتَنافِس عَلَى، مُتَنازَع عَلَى، مُخْتَلَف عَلَى، مَحَلّ نِزاع
274	contesting	صارَع، نازَع، صِراع، نِزاع
275	contraction	اِنْقِباض، تَقَلُّص، تَراجُع، تَضاؤُل، اِنْكِماش
276	contradict	تَناقَض، ناقَض، تَعارَض، عارَض، تَضارَب
277	contradicted	تَناقَض، ناقَض، تَعارَض، عارَض، تَضارَب، مُناقِض، مُتَعارِض، مُتَناقِض
278	contradicting	تَناقَض، ناقَض، تَعارَض، عارَض، تَضارَب، مُناقِض، مُتَعارِض، مُتَناقِض، تَناقُض، تَعارُض، تَضارُب
279	contradiction	تَناقُض، تَعارُض، تَضارُب
280	contradictory	مُتَعارِض، مُتَناقِض، مُناقِض، مُتَبايِن
281	contradicts	تَناقَض، ناقَض، تَعارَض، عارَض، تَضارَب
282	contrary	مُعاكِس، مُعارِض، مُخالِف، مُناقِض، مُتَناقِض، مُضادّ
283	controversial	مُثِير جَدَل، مَوْضِع خِلاف، مُثِير خِلاف، مُتَنازَع عَلَى
284	controversy	نِزاع، خِلاف، جَدَل، جِدال
285	convict	جَرَّم، أدان، مُجْرِم، مُدان
286	convicted	جَرَّم، أدان، مُجْرِم، مُدان
287	convicting	جَرَّم، أدان، تَجْرِيم، مُجْرِم، مُدان
288	conviction	تَجْرِيم، إدانَة
289	corrected	صَحّ، عَدَّل، مُصَحّح
290	correcting	صَحّ، عَدَّل، مُصَحّح، تَصْحِيح، تَعْدِيل
291	correction	تَصْحِيح، تَعْدِيل
292	corrects	صَحّ، عَدَّل
293	corrupt	أفْسَد، فَساد، فاسِد
294	corrupted	أفْسَد، فاسِد
295	corrupting	أفْسَد، فَساد، فاسِد
296	corruption	فَساد
297	corruptly	شَكْل فاسِد، نَحْو فاسِد، صُورَة فاسِد، طَرِيقَة فاسِد
298	corruptness	فَساد

No.	English Word	Arabic Translation
299	costly	مُكَلِّف، غالِي، باهِظ
300	counterclaim	اِدِّعاء مُضادّ، مُطالَبَة مُضادّ، دَعْوَى مُضادّ
301	counterclaimed	اِدِّعاء مُضادّ، مُطالَبَة مُضادّ، دَعْوَى مُضادّ
302	counterclaiming	اِدِّعاء مُضادّ، مُطالَبَة مُضادّ، دَعْوَى مُضادّ
303	counterfeit	زَوَّر، زَيَّف، تَزْوِير، تَزْيِيف، مُزَوَّر، مُزَيَّف
304	counterfeited	زَوَّر، زَيَّف، مُزَوَّر، مُزَيَّف
305	counterfeiter	مُزَيَّف، مُزَوَّر
306	counterfeiting	زَوَّر، زَيَّف، تَزْوِير، تَزْيِيف، مُزَوَّر، مُزَيَّف
307	countermeasure	،إِجْراء مُضادّ، تَدْبِير مُواجَهَة، إِجْراء مُضادّ، تَدْبِير مُضادّ، إِسْتراتِيجِيَّة مُضادّ، تَدْبِير مُضادّ وَسِيلَة مُضادّ
308	crime	جَرِيمَة، جِنايَة
309	criminal	مُجْرِم، إِجْرامِيّ، جِنائِيّ
310	criminally	صُورَة إِجْرامِيّ، نَحْو إِجْرامِيّ، شَكْل إِجْرامِيّ
311	crisis	أَزْمَة، مُصِيبَة
312	critically	شَكْل حَرَج، نَحْو حَرَج، صُورَة حَرِج، طَرِيقَة حَرِج
313	criticism	اِسْتِنْكار، اِنْتِقاد، تَوْبِيخ
314	criticize	اِنْتَقَد
315	criticized	اِنْتَقَد
316	criticizes	اِنْتَقَد
317	criticizing	اِنْتَقَد، اِنْتِقاد
318	crucial	عَصِيب، مِحْوَرِيّ، مَصِير، ضَرُورِيّ، حَرَج
319	crucially	شَكْل ضَرُورِيّ، نَحْو ضَرُورِيّ، صُورَة ضَرُورِيّ
320	culpability	ذَنْب، إِثْم، لَوْم
321	culpable	مُذْنِب، مَلام، مُؤاخَذ
322	culpably	صُورَة مُذْنِب، شَكْل مُذْنِب، نَحْو مُذْنِب
323	cumbersome	شاقّ، مُرْهِق، مُعَقَّد
324	curtail	قَلَّص
325	curtailed	قَلَّص، مُقَلِّص
326	curtailing	قَلَّص، تَقْلِيص، مُقَلِّص
327	curtailment	تَقْلِيص
328	curtails	قَلَّص
329	cut	خَفَّض، قَطَع، وَقَّف
330	cutback	تَقَشُّف، تَقْلِيص، خَفْض
331	cyberattack	هُجُوم مَعْلُومَة
332	cyberattacks	هُجُوم إِلِكْتْرُونِيّ، هَجْمَة مَعْلُوماتِيّ
333	cyberbullying	التَنَمُّر إِلِكْتْرُونِيّ، التَنَمُّر عَبْر إِنْتَرْنِت، التَنَمُّر إِلِكْتْرُونِيّ، مُضايَقَة إِلِكْتْرُونِيّ
334	cybercrime	جَرِيمَة إِلِكْتْرُونِيّ، جَرِيمَة رَقْمِيّ
335	cybercriminal	قُرْص إِلِكْتْرُونِيّ، مُجْرِم إِلِكْتْرُونِيّ، مُخْتَرَق إِلِكْتْرُونِيّ
336	cybercriminals	قُرْص إِلِكْتْرُونِيّ، مُجْرِم إِلِكْتْرُونِيّ، مُخْتَرَق إِلِكْتْرُونِيّ
337	damage	تَلِف، ضَرّ، ضَرَر، تَلَف
338	damaged	تَلِف، ضَرّ، مُتَضَرِّر، تَأَلُّف
339	damaging	تَلِف، ضَرّ، مُتَضَرِّر، تَأَلُّف، ضَرَر، تَلَف
340	dampen	كَبَح، ثَبَط، أَخْمَد
341	dampened	كَبْح، ثَبَط، أَخْمَد
342	danger	خَطَر، تَهْدِيد، خُطُورَة
343	dangerous	خَطِير
344	dangerously	صُورَة خَطِير، شَكْل خَطِير، نَحْو خَطِير، طَرِيقَة خَطَر
345	deadlock	جُمُود، مَأْزِق، طَرِيق مَسْدُود
346	deadlocked	عالِق، مَأْزِق
347	deadlocking	جُمُود، مَأْزِق، عالِق
348	deadweight	عِبْء
349	deadweights	عِبْء غَيْر مُجْدِي، عِبْء

No.	English Word	Arabic Translation
350	debarment	حِرْمان، تَجْرِيد
351	debarred	مَحْظُور، مَمْنُوع، مَحْرُوم
352	deceased	مُتَوَفًّى، مَيِّت
353	deceit	خِداع، تَضْلِيل، اِحْتِيال
354	deceitful	مُخادِع، مُضَلِّل، مُحْتال
355	deceitfulness	خِداع، تَضْلِيل، اِحْتِيال
356	deceive	ضَلَّل، غَشّ، خَدَع
357	deceived	ضَلَّل، غَشّ، خَدَع، مُضَلِّل، مُخادِع
358	deceives	ضَلَّل، غَشّ، خَدَع
359	deceiving	ضَلَّل، غَشّ، خَدَع، خِداع، تَضْلِيل، اِحْتِيال، مُضَلِّل، مُخادِع، مُحْتال
360	deception	خِداع، تَضْلِيل، اِحْتِيال
361	deceptive	مُضَلِّل، مُخادِع، مُحْتال
362	deceptively	شَكْل مُخادِع، نَحْو مُخادِع، صُورَة مُخادِع، طَرِيقَة مُخادِع، شَكْل مُضَلِّل، نَحْو مُضَلِّل، صُورَة مُضَلِّل، طَرِيقَة مُضَلِّل
363	decline	اِنْخَفَض، هَبَط، اِنْحَدَر، تَدَنَّى، تَدَهْوَر، تَراجُع، تَدَهْوُر، هُبُوط، اِنْكِماش، اِنْحِدار، اِنْخِفاض، تَدَنِّي
364	declined	اِنْخَفَض، هَبَط، اِنْحَدَر، تَدَنَّى، تَدَهْوَر، هابِط، مُنْخَفِض، مُتَراجِع، مُتَدَنِّي
365	declining	اِنْخَفَض، هَبَط، اِنْحَدَر، تَدَنَّى، تَدَهْوَر، هابِط، مُنْخَفِض، مُتَراجِع، مُتَدَنِّي، تَراجُع، تَدَهْوُر، هُبُوط، اِنْكِماش، اِنْحِدار، تَدَنِّي
366	deface	شَوَّه، عَبِث، تَلِف، طَمَس
367	defaced	شَوَّه، عَبِث، تَلِف، طَمَس، مَشَى
368	defacement	تَشْوِيه، عَبَث
369	defamation	تَشْهِير، إساءَة، اِفْتِراء، قَذْف
370	defamatory	اِفْتِراء، تَشْهِير
371	defame	شَهَر، أساء، اِفْتَرَى، قَذَف
372	defamed	مَشَى
373	defames	شَهَر، أساء، اِفْتَرَى، قَذَف
374	defaming	شَهَر، أساء، اِفْتَرَى، قَذَف، مَشَى، تَشْهِير، إساءَة، اِفْتِراء، قَذْف
375	default	تَخَلَّف، أَهْمَل، عَجِز، تَخَلُّف، إِهْمال، فَشَل، تَقْصِير، إِخْفاق، عَجْز
376	defaulted	تَخَلَّف، أَهْمَل، عَجِز، مُتَخَلِّف، مُتَعَثِّر، عاجِز
377	defaulting	تَخَلَّف، أَهْمَل، عَجِز، مُتَخَلِّف، مُتَعَثِّر، عاجِز، تَخَلُّف، إِهْمال، فَشَل، تَقْصِير، إِخْفاق، عَجْز
378	defeat	اِنْهَزَم، فَشِل، هَزِيمَة، فَشَل
379	defeated	اِنْهَزَم، فَشِل، فاشِل
380	defeating	اِنْهَزَم، فَشِل، فاشِل، هَزِيمَة، فَشَل
381	defect	عَيْب، خَلَل
382	defective	مُتَضَرِّر، تالِف
383	defend	دافَع
384	defendant	مُتَّهَم، مُدَّعَى عَلَى
385	defended	دافَع
386	defending	دافَع
387	defends	دافَع
388	defensive	دِفاعِيّ، وِقائِيّ
389	defer	أَجَّل، أَرْجَأ، أَحال
390	deficiency	قَصْر، نَقْص، عَجْز، خَلَل
391	deficient	ناقِص، ضَعِيف، عاجِز
392	deficit	عَجْز، نَقْص
393	defraud	اِحْتال، خَدَع، ضَلَّل، اِحْتِيال، تَضْلِيل
394	defrauded	اِحْتال، خَدَع، ضَلَّل
395	defrauding	اِحْتال، خَدَع، ضَلَّل، اِحْتِيال، تَضْلِيل، مُضَلِّل
396	defrauds	اِحْتال، خَدَع، ضَلَّل
397	defunct	مُنْحَلّ، بائِد
398	degradation	تَراجُع، تَدَهْوُر

No.	English Word	Arabic Translation
399	degrade	تَدَهْوَر، خَفَّض، اِنْخَفَض، قَلَّل
400	degraded	مُتَدَهْوِر، مُتَرَدِّي، مُتَدَهْوِر، مُتَراجِع
401	degrades	تَدَهْوَر، خَفَّض، اِنْخَفَض، قَلَّل
402	degrading	تَدَهْوَر، خَفَّض، اِنْخَفَض، قَلَّل
403	delay	أَجَّل، أَرْجَأ، وَخَّر، تَأْجِيل، تَأْخِير
404	delayed	أَجَّل، أَرْجَأ، وَخَّر، مُؤَجَّل، مُتَأَخِّر، مُؤَخَّر
405	delaying	أَجَّل، أَرْجَأ، وَخَّر، مُؤَجَّل، مُتَأَخِّر، مُؤَخَّر، تَأْجِيل، تَأْخِير
406	deleterious	ضارّ، مُؤْذِي، مُضِرّ
407	deliberate	مُتَعَمَّد
408	deliberated	مُتَعَمَّد
409	deliberately	شَكْل مُتَعَمَّد، نَحْو مُتَعَمَّد، صُورَة مُتَعَمَّد، طَرِيقَة مُتَعَمَّد
410	delinquency	تَأَخُّر، إِهْمال، تَقْصِير، جُنُوح
411	delinquent	مُتَعَثِّر، مُتَأَخِّر، مُهْمَل، مُقَصِّر، جانِح
412	delinquently	شَكْل مُتَأَخِّر، نَحْو مُتَأَخِّر، صُورَة مُتَأَخِّر، طَرِيقَة مُتَأَخِّر
413	delist	شَطَب، أَلْغَى إِدْراج
414	delisted	شَطَب، أَلْغَى إِدْراج، مَشْطُوبٌ
415	delisting	شَطَب، أَلْغَى إِدْراج، مَشْطُوبٌ
416	delists	شَطَب، أَلْغَى إِدْراج
417	demise	زَوال
418	demised	زَوال
419	demising	زَوال
420	demolish	هَدَم
421	demolished	هَدَم
422	demolishes	هَدَم
423	demolishing	هَدَم، هَدْم
424	demolition	هَدْم
425	demote	خَفَّض، قَلَّل، نَحَّى
426	demoted	خَفَّض، قَلَّل
427	demotes	خَفَّض، قَلَّل، نَحَّى
428	demoting	خَفَّض، قَلَّل
429	demotion	إِغْلاق، تَصْفِيَة
430	denial	إِنْكار، رَفَض
431	denied	أَنْكَر، رَفَض، مَرْفُوض
432	denies	أَنْكَر، رَفَض
433	denigrate	شَوَّه سُمْعَة
434	denigrated	شَوَّه سُمْعَة
435	denigrates	شَوَّه سُمْعَة
436	denigrating	شَوَّه سُمْعَة، تَشْوِيه سُمْعَة
437	denigration	تَشْوِيه سُمْعَة
438	deny	أَنْكَر، رَفَض
439	denying	أَنْكَر، رَفَض، إِنْكار، رَفْض
440	deplete	اِسْتَنْزَف، اِسْتَنْفَد
441	depleted	اِسْتَنْزَف، اِسْتَنْفَد
442	depletes	اِسْتَنْزَف، اِسْتَنْفَد
443	depleting	اِسْتَنْزَف، اِسْتَنْفَد، اِسْتِنْزاف
444	depletion	اِسْتِنْزاف، نُضُوب
445	deprecation	تَقْلِيل، اِنْخِفاض قِيمَة، اِسْتِنْكار
446	depress	قَلَّل، ضَغَط، خَفَّض، ثَبَط
447	depressed	قَلَّل، ضَغَط، خَفَّض، ثَبَط
448	depresses	قَلَّل، ضَغَط، خَفَّض، ثَبَط
449	depressing	قَلَّل، ضَغَط، خَفَّض، ثَبَط، مُحْبِط
450	deprivation	فِقْدان، حِرْمان، اِفْتِقار

No.	English Word	Arabic Translation
451	deprive	جَرَّد، حَرَم
452	deprived	جَرَّد، حَرَم، مَحْرُوم
453	deprives	جَرَّد، حَرَم
454	depriving	جَرَّد، حَرَم، حِرْمان، تَجْرِيد
455	derelict	مَهْجُور، مُهْمَل، مُهْمَل
456	dereliction	إِهْمال، تَقْصِير
457	derogatory	مُهِين، مُسِيء
458	destabilization	عَدَم إِسْتِقْرار، زَعْزَعَة
459	destabilize	زَعْزَع إِسْتِقْرار، خَلا إِسْتِقْرار
460	destabilized	زَعْزَع إِسْتِقْرار، خَلا إِسْتِقْرار، مُزَعْزَع، مُضْطَرِب، غَيْر مُسْتَقِرّ
461	destabilizing	زَعْزَع إِسْتِقْرار، خَلا إِسْتِقْرار، مُزَعْزَع، مُضْطَرِب، غَيْر مُسْتَقِرّ، عَدَم إِسْتِقْرار، زَعْزَعَة
462	destroy	دَمَّر، تَلِف، خَرَّب
463	destroyed	دَمَّر، تَلِف، خَرَّب، مُدَمِّر، تَأَلَّف
464	destroying	دَمَّر، تَلِف، خَرَّب، مُدَمِّر، تَأَلَّف، إِتْلاف، تَخْرِيب
465	destroys	دَمَّر، تَلِف، خَرَّب
466	destruction	خَراب، تَدْمِير، دَمار
467	destructive	هَدّام، مُدَمِّر
468	detain	إِسْتَوْقَف، إِعْتَقَل، إِحْتَجَز
469	detained	إِسْتَوْقَف، إِعْتَقَل، إِحْتَجَز، مَوْقُوف، مُعْتَقَل، مُحْتَجَز
470	detention	إِعْتِقال، إِحْتِجاز
471	deter	مَنَع، رَدَع
472	deteriorate	تَدَهْوَر، تَرَدَّى
473	deteriorated	تَدَهْوَر، تَرَدَّى
474	deteriorates	تَدَهْوَر، تَرَدَّى
475	deteriorating	تَدَهْوَر، تَرَدَّى، مُتَدَهْوِر، مُتَرَدِّي، تَدَهْوُر
476	deterioration	تَدَهْوُر
477	deterred	مَنَع، رَدَع، ثَنَى
478	deterrence	رَدْع
479	deterrent	رادِع
480	deterring	مَنَع، رَدَع، ثَنَى
481	deters	مَنَع، رَدَع، ثَنَى
482	detract	إِنْتَقَص، قَلَّل
483	detracted	إِنْتَقَص، قَلَّل
484	detracting	إِنْتَقَص، قَلَّل، إِنْتِقاص
485	detriment	أَذَى، ضَرَر
486	detrimental	ضارّ، مُؤْذِي
487	detrimentally	طَرِيقَة ضارّ، صُورَة مُضِرّ، شَكْل ضارّ، نَحْو ضارّ، شَكْل مُؤْذِي، صُورَة مُؤْذِي، طَرِيقَة مُؤْذِي، نَحْو مُؤْذِي
488	devalue	نَقَص قِيمَة، قَلَّل قِيمَة، خَفَّض قِيمَة
489	devalued	نَقَص قِيمَة، قَلَّل قِيمَة، خَفَّض قِيمَة، مُنْخَفِض قِيمَة
490	devalues	نَقَص قِيمَة، قَلَّل قِيمَة، خَفَّض قِيمَة
491	devaluing	نَقَص قِيمَة، قَلَّل قِيمَة، خَفَّض قِيمَة، مُنْخَفِض قِيمَة، تَخْفِيض قِيمَة، تَقْلِيل قِيمَة
492	devastate	دَمَّر، خَرَّب
493	devastated	دَمَّر، خَرَّب، مُدَمِّر، مُحَطِّم
494	devastating	دَمَّر، خَرَّب، مُدَمِّر، مُحَطِّم، وَخِيم
495	devastation	دَمار، خَراب
496	deviate	حَيَّد، شَذَّ، إِنْحَرَف
497	deviated	حَيَّد، شَذَّ، إِنْحَرَف، مُنْحَرِف
498	deviating	حَيَّد، شَذَّ، إِنْحَرَف، مُنْحَرِف، إِنْحِراف، شَذّ
499	deviation	إِنْحِراف، شَذّ
500	devolve	نَحَل، آل، إِنْحَدَر، تَدَنَّى
501	devolved	نَحَل، آل، إِنْحَدَر، تَدَنَّى، مُتَدَهْوِر، مُنْحَدَر

No.	English Word	Arabic Translation
502	devolves	نَحَل، آل، اِنْحَدَر، تَدَنَّى
503	devolving	نَحَل، آل، اِنْحَدَر، تَدَنَّى
504	difficult	شاقّ، صَعْب
505	difficultly	شَكْل صَعْب، نَحْو صَعْب، صُورَة صَعْب، طَرِيقَة صَعْب، شَكْل شاقّ، نَحْو شاقّ، صُورَة شاقّ، طَرِيقَة شاقّ
506	difficulty	عائِق، صُعُوبَة
507	diminish	قَلَّل، تَضاءَل
508	diminished	تَضاءَل، قَلَّل، خَفَّض
509	diminishes	تَضاءَل، قَلَّل، خَفَّض
510	diminishing	تَضاءَل، قَلَّل، خَفَّض، تَضاؤُل
511	diminution	نُقْصان، تَضاؤُل
512	disadvantage	عَيْب، مَساءَة، عائِق
513	disadvantaged	مَحْرُوم، مُتَضَرِّر، ناقِص
514	disadvantageous	ضارّ، مُضِرّ، غَيْر مُفِيد، عَدِيم فائِدَة، غَيْر مُؤاتِي، غَيْر مَلام
515	disaffiliation	اِنْفِصال، عَدَم اِنْتِماء، قَطْع صِلَة، فَكّ اِرْتِباط
516	disagree	رَفَض، تَعارَض، اِعْتَرَض، اِخْتَلَف، ناقَض، لا وافَق، لا اِتَّفَق
517	disagreeable	مُزْعِج، غَيْر مَقْبُول، غَيْر مَرْغُوب فِي، غَيْر مُتَّفَق عِلَيَة
518	disagreed	رَفَض، تَعارَض، اِعْتَرَض، اِخْتَلَف، ناقَض، لا وافَق، لا اِتَّفَق
519	disagreeing	رَفَض، تَعارَض، اِعْتَرَض، اِخْتَلَف، ناقَض
520	disagreement	خِلاف، نِزاع، تَعارُض
521	disagrees	رَفَض، تَعارَض، اِعْتَرَض، اِخْتَلَف، ناقَض، لا وافَق، لا اِتَّفَق
522	disallow	رَفَض، مَنَع، حَظَر، لا أَقَرّ، لا سَمَح
523	disallowance	رَفْض، مَنْع، عَدَم سَماح، عَدَم مُوافَقَة
524	disallowances	رَفْض، مَنْع، عَدَم سَماح، عَدَم مُوافَقَة
525	disallowed	رَفَض، مَنَع، حَظَر، مَرْفُوض، مَحْظُور، مَرْفُوض، مَمْنُوع، غَيْر مَسْمُوح بِ، غَيْر مَقْبُول، غَيْر مَسْمُوح
526	disallowing	رَفَض، مَنَع، حَظَر، مَرْفُوض، مَحْظُور، مَرْفُوض، مَمْنُوع، غَيْر مَسْمُوح بِ، غَيْر مَقْبُول، غَيْر مَسْمُوح
527	disallows	رَفَض، مَنَع، حَظَر، لا أَقَرّ، لا سَمَح
528	disappear	اِضْمَحَلّ، تَوارَى، اِخْتَفَى، تَلاشَى
529	disappearance	تَلاشِي، اِخْتِفاء
530	disappeared	اِخْتَفَى، تَلاشَى، مُخْتَفَى
531	disappearing	اِخْتَفَى، تَلاشَى، تَلاشِي، اِخْتِفاء
532	disappears	اِخْتَفَى، تَلاشَى
533	disappoint	حَبَط، خاب، خَذَل
534	disappointed	حَبَط، خاب، خَذَل، مُحْبِط
535	disappointing	حَبَط، خاب، خَذَل، مُحْبِط، إِحْباط، خِذْلان
536	disappointingly	شَكْل مُحْبِط، صُورَة مُحْبِط، طَرِيقَة مُحْبِط، نَحْو مُحْبِط، شَكْل مُؤْسِف، صُورَة مُؤْسِف، نَحْو مُؤْسِف، طَرِيقَة مُؤْسِف
537	disappointment	إِحْباط، خِذْلان، خَيْبَة أَمَل
538	disappoints	حَبَط، خاب، خَذَل
539	disapproval	رَفْض، اِسْتِنْكار، عَدَم مُوافَقَة، عَدَم رِضَى
540	disapprove	رَفَض، اِسْتَنْكَر، لا وافَق
541	disapproved	رَفَض، اِسْتَنْكَر، مَرْفُوض
542	disapproves	رَفَض، اِسْتَنْكَر، لا وافَق
543	disapproving	رَفَض، اِسْتَنْكَر، لا وافَق، رَفْض، عَدَم مُوافَقَة
544	disassociates	نَأَى، تَبَرَّأ، اِنْفَصَل
545	disassociating	نَأَى، تَبَرَّأ، اِنْفَصَل، قَطْع عَلاقَة
546	disassociation	تَفَكُّك، اِنْفِصال، قَطْع عَلاقَة
547	disaster	بَلاء، كارِثَة، مُصِيبَة، فاجِع
548	disastrous	فاجِع، فادِح، مَأْسَوِيّ، كارِثي
549	disastrously	شَكْل فادِح، نَحْو فادِح، طَرِيقَة فادِح، صُورَة فادِح

No.	English Word	Arabic Translation
550	disavow	أَنْكَر، تَنَصَّل، تَبَرَّأ
551	disavowal	إِنْكار، تَنَصَّل
552	disavowed	أَنْكَر، تَنَصَّل، تَبَرَّأ
553	disavowing	أَنْكَر، تَنَصَّل، تَبَرَّأ، إِنْكار، التَّنَصُّلُ
554	disavows	أَنْكَر، تَنَصَّل، تَبَرَّأ
555	disciplinary	اِنْضِباط، تَأْدِيب، تَأْدِيب
556	disclaim	تَنَصَّل، تَبَرَّأ، نَفَى، أَخْلَى مَسْؤُولِيَّة
557	disclaimed	تَنَصَّل، تَبَرَّأ، نَفَى، أَخْلَى مَسْؤُولِيَّة
558	disclaimer	إِخْلاء مَسْؤُولِيَّة
559	disclaiming	تَنَصَّل، تَبَرَّأ، نَفَى، أَخْلَى مَسْؤُولِيَّة، إِخْلاء مَسْؤُولِيَّة
560	disclaims	تَنَصَّل، تَبَرَّأ، نَفَى، أَخْلَى مَسْؤُولِيَّة
561	disclose	أَفْصَح، أَفْشَى
562	disclosed	أَفْصَح، أَفْشَى
563	discloses	أَفْصَح، أَفْشَى
564	disclosing	أَفْصَح، أَفْشَى، إِفْشاء
565	discontinuance	اِنْقِطاع، إِيقاف، تَوَقُّف
566	discontinuation	تَخارُج، إِيقاف، تَوَقُّف
567	discontinue	وَقَّف، أَنْهَى، اِنْقَطَع
568	discontinued	وَقَّف، أَنْهَى، اِنْقَطَع، مَوْقُوف، مُتَوَقِّف
569	discontinues	وَقَّف، أَنْهَى، اِنْقَطَع
570	discontinuing	وَقَّف، أَنْهَى، اِنْقَطَع، مَوْقُوف، مُتَوَقِّف، إِيقاف، اِنْقِطاع
571	discourage	حَبَط، نَفَر، ثَنَى، ثَبَط، إِحْباط
572	discouraged	حَبَط، نَفَر، ثَنَى، ثَبَط، مُحْبِط، مُثَبِّطٌ
573	discourages	حَبَط، نَفَر، ثَنَى، ثَبَط
574	discouraging	حَبَط، نَفَر، ثَنَى، ثَبَط، مُحْبِط، مُثَبِّطٌ، إِحْباط
575	discredit	أَضْعَف سُمْعَة، شَوَّه سُمْعَة، أَساء سُمْعَة، أَفْقَد مِصْداقِيَّة، جَرَّد مِن ثِقَة
576	discredited	أَضْعَف سُمْعَة، شَوَّه سُمْعَة، أَساء سُمْعَة، أَفْقَد مِصْداقِيَّة
577	discrediting	أَضْعَف سُمْعَة، شَوَّه سُمْعَة، أَساء سُمْعَة، أَفْقَد مِصْداقِيَّة، فِقْدان ثِقَة
578	discrepancy	تَفاوُت، تَبايُن، تَضارُب، اِخْتِلاف، تَناقُض
579	disfavor	عارَض، لا اِسْتَحْسَن، اِسْتِياء، عَدَم اِسْتِحْسان
580	disfavored	عارَض، لَم اِسْتَحْسَن، غَيْر مَرْغُوب بِ، غَيْر مُفَضَّل، غَيْر مُسْتَحْسَن
581	disfavoring	عارَض، لا اِسْتَحْسَن، تَحَيَّز ضِدّ، غَيْر مَرْغُوب بِ، غَيْر مُفَضَّل، غَيْر مُسْتَحْسَن، اِسْتِياء، عَدَم اِسْتِحْسان
582	disgorge	أَعاد رِبْح، تَخَلَّى عَن رِبْح، أَجْبَر عَلَى إِعادَة، أَلْزَم دَفْع
583	disgorged	أَعاد رِبْح، تَخَلَّى عَن رِبْح، أَجْبَر عَلَى إِعادَة، أَلْزَم دَفْع
584	disgorgement	رِبْح غَيْر مَشْرُوع، تَعْوِيض
585	disgorges	أَعاد رِبْح، تَخَلَّى عَن رِبْح، أَجْبَر عَلَى إِعادَة، أَلْزَم دَفْع
586	disgorging	أَعاد رِبْح، تَخَلَّى عَن رِبْح، أَجْبَر عَلَى إِعادَة، أَلْزَم دَفْع، إِعادَة إِجْبارِيّ
587	disgrace	خِزْي، عار، فَضِيحَة
588	disgraceful	مُهِين، مَشَى، مَخْزِيّ، مُثِير اِشْمِئْزاز
589	disgracefully	شَكْل مُهِين، نَحْو مُهِين
590	dishonest	غَيْر أَمِين، غَيْر صادِق
591	dishonestly	شَكْل مُخادِع، نَحْو مُخادِع
592	dishonesty	كِذْب، خِداع، عَدَم صِدْق، عَدَم أَمانَة
593	dishonor	خَزَى، أَهان
594	dishonorable	مَخْزِيّ، غَيْر شَرِيف، غَيْر أَخْلاقِيّ
595	dishonorably	شَكْل مَخْزِيّ، نَحْو مَخْزِيّ، طَرِيقَة غَيْر شَرِيف، صُورَة غَيْر شَرِيف
596	dishonored	مَخْزِيّ، أَهان، مُهِين
597	dishonoring	خَزَى، أَهان، مُهِين، إِهانَة
598	disincentives	مُثَبِّطٌ، غَيْر مُشَجِّع
599	disinterested	غَيْر مُهْتَمّ، غَيْر مُبالِي
600	disinterestedly	شَكْل لا مُبالِي، شَكْل غَيْر مُبالِي

No.	English Word	Arabic Translation
601	disinterestedness	عَدَم اِهْتِمام
602	disloyal	خائِن، غَيْر أمِين، غَيْر مُخْلِص
603	disloyally	شَكْل غَيْر مُخْلِص، نَحْو غَيْر مُخْلِص
604	disloyalty	خِيانَة، عَدَم إخْلاص، عَدَم وَلاء، عَدَم وَفاء
605	dismal	كَئِيب، مُحْبِط، سَيِّء
606	dismally	شَكْل سَيِّء، نَحْو سَيِّء، صُورَة سَيِّء، شَكْل مُحْبِط، نَحْو مُحْبِط، صُورَة مُحْبِط
607	dismiss	طَرَد، رَفَض
608	dismissal	إقالَة، تَسْرِيح، طَرْد
609	dismissed	طَرَد، رَفَض، تَمّ رَفْض، مُسْتَبْعَد
610	dismisses	طَرَد، رَفَض
611	dismissing	طَرَد، رَفَض، إقالَة، تَسْرِيح، طَرْد
612	disorderly	فَوْضَوِيّ، عَشْوائِيّ، شَكْل غَيْر مُنَظَّم
613	disparage	اِحْتَقَر، اِنْتَقَص، اِسْتَهْزَأ، تَحْقِير، اِنْتِقاص، اِسْتِخْفاف
614	disparaged	اِحْتَقَر، اِنْتَقَص، اِسْتَهْزَأ
615	disparagement	اِزْدِراء، اِسْتِخْفاف، اِسْتِهْزاء
616	disparages	اِنْتَقَص، سَخَّر، اِحْتَقَر
617	disparaging	اِحْتَقَر، اِنْتَقَص، اِسْتَهْزَأ، تَحْقِير، اِنْتِقاص، اِسْتِخْفاف
618	disparagingly	شَكْل اِزْدِراء، نَحْو اِزْدِراء، صُورَة اِزْدِراء، طَرِيقَة اِزْدِراء
619	disparity	تَبايُن، تَغايُر، تَفاوُت
620	displace	زاح
621	displaced	مَزّاح، مُسْتَبْدَل
622	displacement	إزاحَة، اِسْتِبْدال، إحْلال
623	displaces	زاح
624	displacing	زاح، مُسْتَبْدَل
625	dispose	تَخَلَّص، تَخَلَّص
626	dispossess	صادَر، نَزَع، جَرَّد، اِنْتَزَع
627	dispossessed	صادَر، نَزَع، جَرَّد، اِنْتَزَع، مَصادَر، مَنْزُوع
628	dispossesses	صادَر، نَزَع، جَرَّد، اِنْتَزَع
629	dispossessing	صادَر، نَزَع، جَرَّد، اِنْتَزَع، مَصادَر، مَنْزُوع
630	disproportion	تَفاوُت، اِخْتِلال، عَدَم تَوازُن، عَدَم تَناسُب
631	disproportional	غَيْر مُتَساوِي، غَيْر مُتَوازِن، غَيْر مُتَكافِئ، غَيْر مُتَناسِب، غَيْر مُتَجانِس
632	disproportionate	،غَيْر مُتَساوِي، غَيْر مُتَناسِب، غَيْر مُتَناسِب، غَيْر مُتَوازِن، غَيْر مُتَناسِب، غَيْر مُتَكافِئ غَيْر مُتَجانِس
633	disproportionately	شَكْل غَيْر مُتَناسِب، شَكْل غَيْر مُتَساوِي، شَكْل غَيْر مُتَوازِن، شَكْل غَيْر مُتَكافِئ، شَكْل غَيْر مُتَجانِس
634	dispute	جادَل، نازَع، اِعْتَرَض، جِدال، اِعْتِراض، خِلاف، نِزاع
635	disputed	جادَل، نازَع، اِعْتَرَض، مَحَلّ جِدال، مُتَنازَع عَلَى، مَحَلّ خِلاف
636	disputing	جادَل، نازَع، اِعْتَرَض، جِدال، اِعْتِراض، خِلاف، نِزاع
637	disqualification	إلْغاء أهْلِيَّة، فِقْدان أهْلِيَّة، عَدَم أهْلِيَّة، تَجْرِيد مِن أهْلِيَّة
638	disqualified	فاقِد أهْلِيَّة، غَيْر مُؤَهَّل، مُلْغَى أهْلِيَّة، مُسْتَبْعَد، مُنْسَحِب
639	disqualifies	اِسْتَبْعَد، قَرَّر عَدَم أهْلِيَّة، جَرَّد مِن أهْلِيَّة، أفْقَد أهْلِيَّة
640	disqualify	اِسْتَبْعَد، قَرَّر عَدَم أهْلِيَّة، جَرَّد مِن أهْلِيَّة، أفْقَد أهْلِيَّة، عَدَم أهْلِيَّة، غَيْر مُؤَهَّل
641	disqualifying	إلْغاء أهْلِيَّة، فِقْدان أهْلِيَّة، عَدَم أهْلِيَّة، تَجْرِيد مِن أهْلِيَّة
642	disregard	تَغاضَى، تَجاهَل، تَغافَل، أهْمَل، تَجاهُل، اِسْتِخْفاف، إهْمال
643	disregarded	تَغاضَى، تَجاهَل، تَغافَل، أهْمَل، مُهْمَل
644	disregarding	تَغاضَى، تَجاهَل، تَغافَل، أهْمَل، مُهْمَل، تَجاهُل، اِسْتِخْفاف، إهْمال
645	disreputable	سَيِّء سُمْعَة، ضارّ سُمْعَة
646	disrepute	عار، سَيِّء سُمْعَة، سُمْعَة سَيِّء
647	disrupt	عَرْقَل، شَوَّش، أرْبَك
648	disrupted	عَرْقَل، شَوَّش، أرْبَك، مُرْبِك
649	disrupting	عَرْقَل، شَوَّش، أرْبَك، مُرْبِك
650	disruption	عَرْقَلَة، إرْباك، إخْلال

No.	English Word	Arabic Translation
651	disruptive	مُعَرْقِل، مُرْبِك
652	disrupts	عَرْقَل، شَوَّش، أَرْبَك
653	dissatisfaction	اِسْتِياء، سُخْط، تَذَمُّر، اِمْتِعاض، عَدَم رِضَى
654	dissatisfied	مُمْتَعِض، غَيْر راضِي، عَدَم رِضَى، مُسْتاء
655	dissent	عارَض، اِنْشَقّ، مُعارَضَة
656	dissented	عارَض، اِنْشَقّ، مُنْشَقّ، مُعارِض
657	dissenter	مُعارِض، مُنْشَقّ
658	dissenting	عارَض، اِنْشَقّ، مُنْشَقّ، مُعارِض، مُعارَضَة
659	dissident	مُعارِض، مُنْشَقّ
660	dissolution	تَصْفِيَة
661	distort	شَوَّه، زَيَّف، حَرَّف
662	distorted	شَوَّه، زَيَّف، حَرَّف، مَشَى، مُزَيَّف، مُحَرَّف، تَشْوِيه، تَزْيِيف، تَحْرِيف
663	distorting	شَوَّه، زَيَّف، حَرَّف، مَشَى، مُزَيَّف، مُحَرَّف
664	distortion	تَشْوِيه، تَزْيِيف، تَحْرِيف
665	distorts	شَوَّه، زَيَّف، حَرَّف
666	distract	أَرْبَك، شَتّ
667	distracted	أَرْبَك، شَتّ
668	distracting	أَرْبَك، شَتّ
669	distraction	إِرْباك
670	distracts	أَرْبَك، شَتّ
671	distress	ضائِقَة، مِحْنَة، شِدَّة
672	distressed	مُتَعَثِّر
673	disturb	شَوَّش، اِضْطَرَب، أَقْلَق، عاق
674	disturbance	اِضْطِراب
675	disturbed	مُضْطَرِب، غَيْر مُسْتَقِرّ، مُقْلِق
676	disturbing	شَوَّش، اِضْطَرَب، أَقْلَق، عاق، مُقْلِق
677	disturbs	شَوَّش، اِضْطَرَب، أَقْلَق، عاق
678	diversion	اِنْحِراف، تَضْلِيل، تَشْتِيت
679	divert	لَها، اِنْحَرَف، بَعُد
680	diverted	لَها، اِنْحَرَف، بَعُد
681	diverting	لَها، اِنْحَرَف، بَعُد، مُنْحَرِف
682	diverts	لَها، اِنْحَرَف، بَعُد
683	divest	جَرَّد، تَخَلَّص، تَجَرَّد
684	divested	جَرَّد، تَخَلَّص، تَجَرَّد
685	divesting	جَرَّد، تَخَلَّص، تَجَرَّد
686	divestiture	تَصْفِيَة، تَجْرِيد
687	divestment	تَصْفِيَة
688	divestments	تَصْفِيَة
689	divests	جَرَّد، تَخَلَّص، تَجَرَّد
690	divorce	طَلاق
691	divorced	مُنْفَصِل
692	divulge	أَفْشَى
693	divulged	أَفْشَى، مُفْشَى
694	divulges	أَفْشَى
695	divulging	أَفْشَى
696	doubt	شَكّ، شَكَّك، اِرْتاب، رَيْب، تَرَدُّد، شَكّ
697	doubted	شَكّ، شَكَّك، مَشْكُوك بِ، مُشَكِّك بِ
698	doubtful	مُبْهَم، مُتَرَدِّد، مَشْكُوك، غَيْر مُؤَكِّد، مَوْضِع شَكّ، مَحَلّ شَكّ
699	downgrade	خَفَّض، قَلَّل، تَخْفِيض، تَقْلِيل
700	downgraded	خَفَّض، قَلَّل، مُخَفَّض
701	downgrading	خَفَّض، قَلَّل، مُخَفَّض، تَخْفِيض، تَقْلِيل
702	downsize	خَفَّض، قَلَّص، تَخْفِيض، تَقْلِيص

No.	English Word	Arabic Translation
703	downsized	خَفَّض، قَلَّص، تَخْفِيض، تَقْلِيص، مُخَفَّض، مُنْكَمِش
704	downsizes	خَفَّض، قَلَّص
705	downsizing	خَفَّض، قَلَّص، تَخْفِيض، تَقْلِيص
706	downtime	تَوَقُّف، تَعَطُّل
707	downturn	رُكُود، اِنْكِماش
708	downward	هابِط
709	downwards	هابِط
710	drag	جَرّ، سَحَب، عَرْقَل
711	drastic	عَنِيف، حادّ، قاسِي
712	drastically	شَكْل حادّ، نَحْو حادّ، صُورَة حادّ، طَرِيقَة حادّ
713	drawback	عائِق، عَقَبَة، عَيْب
714	dropped	تَراجَع، هَبَط، اِنْخَفَض، مُتَراجِع، هابِط، مُنْخَفِض
715	drought	جَفاف، شُحّ
716	duress	أَرْغَم، أَجْبَر، إِرْغام، إِجْبار
717	dysfunction	عَجْز، قُصْر، خَلَل
718	dysfunctional	مُعَطَّل، مُخْتَلّ، مُضْطَرِب
719	easing	خَفَّف، تَخْفِيف
720	egregious	بَشِع، شَنِيع
721	egregiously	شَكْل شَنِيع، نَحْو شَنِيع، شَكْل بَشِع، نَحْو بَشِع
722	embargo	قاطَع، حَظَر، مَنَع، مُقاطَعَة، حَظْر، مَنْع
723	embargoed	قاطَع، حَظَر، مَنَع، مَمْنُوع، مَحْظُور
724	embargoing	قاطَع، حَظَر، مَنَع، مَمْنُوع، مَحْظُور، مُقاطَعَة، حَظْر، مَنْع
725	embarrass	أَحْرَج
726	embarrassed	أَحْرَج، مُحْرِج، مُخْجِل
727	embarrasses	أَحْرَج
728	embarrassing	أَحْرَج، مُحْرِج، مُخْجِل، حَرَج
729	embarrassment	حَرَج
730	embezzle	اِخْتَلَس، سَرَق
731	embezzled	اِخْتَلَس، سَرَق، مُخْتَلَس، مَسْرُوق
732	embezzlement	اِخْتِلاس
733	embezzler	مُخْتَلَس
734	embezzles	اِخْتَلَس، سَرَق
735	embezzling	اِخْتَلَس، سَرَق، مُخْتَلَس، مَسْرُوق، اِخْتِلاس
736	encroach	تَعَدَّى، اِنْتَهَك
737	encroached	تَعَدَّى، اِنْتَهَك
738	encroaches	اِعْتَدَى، اِنْتَهَك
739	encroaching	اِعْتَدَى، اِنْتَهَك، تَعَدِّي، اِنْتِهاك
740	encroachment	تَعَدِّي، اِنْتِهاك
741	encumber	أَثْقَل
742	encumbered	أَثْقَل
743	encumbering	أَثْقَل
744	encumbers	أَثْقَل
745	encumbrance	عِبْء
746	endanger	هَدَّد
747	endangered	هَدَّد
748	endangering	هَدَّد
749	endangerment	خَطَر
750	endangers	هَدَّد
751	enjoin	أَلْزَم، أَمَر
752	enjoined	أَلْزَم، أَمَر
753	enjoining	أَلْزَم، أَمَر، إِلْزام
754	enjoins	أَلْزَم، أَمَر

No.	English Word	Arabic Translation
755	erode	تَآكَل
756	eroded	تَآكَل، مُتَآكِل
757	erodes	تَآكَل
758	eroding	تَآكَل، مُتَآكِل
759	erosion	تَآكُل
760	erratic	مُتَذَبْذِب، مُتَقَلِّب
761	erratically	شَكْل غَيْر مُنْتَظِم، طَرِيقَة غَيْر مُنْتَظِم، صُورَة غَيْر مُنْتَظِم، نَحْو غَيْر مُنْتَظِم، شَكْل مُتَذَبْذِب، نَحْو مُتَذَبْذِب
762	erred	أَخْطَأ
763	erring	أَخْطَأ
764	erroneous	خاطِئ، مَغْلُوط
765	erroneously	شَكْل خاطِئ، نَحْو خاطِئ، صُورَة خاطِئ، شَكْل مَغْلُوط، نَحْو مَغْلُوط، صُورَة مَغْلُوط، طَرِيقَة مَغْلُوط
766	error	خَطَأ
767	errs	أَخْطَأ
768	escalate	تَفاقَم، صَعَّد
769	escalated	تَفاقَم، صَعَّد، مُتَفاقِم
770	escalates	تَفاقَم، صَعَّد
771	escalating	تَفاقَم، صَعَّد، تَصْعِيد، مُتَفاقِم
772	evade	تَهَرَّب، تَمَلَّص، راوَغ
773	evaded	تَهَرَّب، تَمَلَّص، راوَغ
774	evades	تَهَرَّب، تَمَلَّص، راوَغ
775	evading	تَهَرَّب، تَمَلَّص، راوَغ
776	evasion	تَهَرُّب، تَمَلُّص، مُراوَغَة
777	evasive	مُتَهَرِّبٌ
778	evict	طَرَد، جَلَى
779	evicted	طَرَد، جَلَى، مَطْرُود
780	evicting	طَرَد، جَلَى
781	eviction	طَرْد، إِجْلاء، إِخْلاء
782	evicts	طَرَد، جَلَى
783	exacerbate	اِسْتَفْحَل، تَفاقَم، أَزَّم
784	exacerbated	اِسْتَفْحَل، تَفاقَم، أَزَّم
785	exacerbates	اِسْتَفْحَل، تَفاقَم، أَزَّم
786	exacerbating	اِسْتَفْحَل، تَفاقَم، أَزَّم
787	exacerbation	تَأْزِيم
788	exaggerate	ضَخَّم، بالَغ
789	exaggerated	ضَخَّم، بالَغ
790	exaggerates	ضَخَّم، بالَغ
791	exaggerating	ضَخَّم، بالَغ
792	exaggeration	تَضْخِيم، مُبالَغَة
793	excessive	مُفْرِط
794	excessively	شَكْل مُفْرِط، نَحْو مُفْرِط
795	exculpate	بَرَّأ
796	exculpated	بَرَّأ
797	exculpates	بَرَّأ
798	exculpating	بَرَّأ، بَراءَة
799	exculpation	تَبْرِئَة
800	exculpatory	تَبْرِئَة
801	exonerate	بَرَّأ
802	exonerated	بَرَّأ
803	exonerates	بَرَّأ
804	exonerating	بَرَّأ

No.	English Word	Arabic Translation
805	exoneration	تبْرِئَة
806	exploit	اِنْتَهَز
807	exploitation	اِنْتِهاز
808	exploitative	اِنْتِهازِيّ
809	exploited	اِنْتَهَز
810	exploiting	اِنْتَهَز، اِنْتِهاز
811	expose	فَضَح، أفْشَى، عَرَّض
812	exposed	فَضَح، أفْشَى، عَرَّض
813	exposing	فَضَح، أفْشَى، عَرَّض
814	expropriate	اِنْتَزَع، صادَر
815	expropriated	اِنْتَزَع، صادَر، مُنْتَزَع، مَصادَر
816	expropriates	اِنْتَزَع، صادَر، مُنْتَزَع، مَصادَر
817	expropriating	اِنْتَزَع، صادَر، مُنْتَزَع، مَصادَر، مُصادَر، اِنْتِزاع
818	expropriation	مُصادَر، اِنْتِزاع
819	expulsion	طَرْد
820	extenuating	تَخْفِيف
821	fail	خَفَق، فَشِل، عَجِز
822	failed	خَفَق، فَشِل، عَجِز
823	failing	خَفَق، فَشِل، عَجِز، إخْفاق، فَشَل، عَجْز
824	fails	خَفَق، فَشِل، عَجِز
825	failure	إخْفاق، فَشَل، عَجْز، قُصُور
826	fallout	تَداعِي، عاقِبَة، فَشَل
827	false	مُضَلِّل، زائِف، كاذِب، خاطِئ
828	falsely	شَكْل خاطِئ، طَرِيقَة خاطِئ، نَحْو خاطِئ، شَكْل مُزَيَّف، طَرِيقَة مُزَيَّف، نَحْو مُزَيَّف
829	falsification	تَزْيِيف، تَزْوِير، تَحْرِيف
830	falsified	زَيَّف، زَوَّر، حَرَّف، مُزَيَّف، مُزَوَّر، مُحَرَّف
831	falsifies	زَيَّف، زَوَّر، حَرَّف
832	falsify	كِذْب، تَحْرِيف، تَزْيِيف
833	falsifying	زَيَّف، زَوَّر، حَرَّف، مُزَيَّف، مُزَوَّر، مُحَرَّف، تَزْيِيف، تَزْوِير، تَحْرِيف
834	falsity	زَيَّف، زَوَّر، حَرَّف
835	fatality	فاجِع، وَفاة
836	fatally	شَكْل مُدَمِّر، نَحْو مُدَمِّر، شَكْل قاتِل، نَحْو قاتِل
837	fault	لام، اِنْتَقَد، خَطَأ، عَيْب، خَلَل، قُصْر
838	faulted	لام، اِنْتَقَد
839	faulty	خاطِئ
840	fear	خاف، خَشِي، خَوْف، خَشْيَة
841	felonious	إجْرامِيّ
842	felony	جِنايَة، جَرِيمَة
843	fictitious	زائِف، كاذِب
844	fines	غَرِم، غَرامَة
845	fined	غَرِم، مَغْرَم
846	fired	مَفْصُول، مَطْرُود
847	firing	إقالَة
848	flaw	خَلَل، عَيْب
849	flawed	مُعْتَلّ
850	forbid	مَنَع، حَرَم، حَظَر
851	forbidden	مَنَع، حَرَم، حَظَر، مَمْنُوع، مَحْظُور
852	forbidding	مَنَع، حَرَم، حَظَر، مَمْنُوع، مَحْظُور
853	forbids	مَنَع، حَرَم، حَظَر
854	forced	أجْبَر، اِضْطَرّ، فَرَض، مُجْبَر، مُضْطَرّ
855	forcing	أجْبَر، اِضْطَرّ، فَرَض، مُجْبَر، مُضْطَرّ
856	foreclose	نَزَع، صادَر، حَبَس رَهْن

No.	English Word	Arabic Translation
857	foreclosed	نَزَع، صادَر
858	forecloses	نَزَع، صادَر
859	foreclosing	نَزَع، صادَر
860	foreclosure	مَصادَر
861	forego	تنازَل عَن، تَخَلّى عَن، اِسْتَغْنَى عَن
862	foregoes	تنازَل عَن، تَخَلّى عَن، اِسْتَغْنَى عَن
863	foregone	مُتَنازِل عَن، مُسْتَغْنَى عَن
864	forestall	اِسْتَبْقَى، تَحاشَى
865	forestalled	اِسْتَبْقَى، تَحاشَى
866	forestalling	اِسْتَبْقَى، تَحاشَى
867	forestalls	اِسْتَبْقَى، تَحاشَى
868	forfeit	أَفْقَد، اِنْسَحَب، صادَر
869	forfeited	أَفْقَد، اِنْسَحَب، صادَر، مَصادَر
870	forfeiting	أَفْقَد، اِنْسَحَب، صادَر، مَصادَر
871	forfeiture	مُصادَر
872	forgers	مُزَوَّر
873	forgery	تَزْوِير
874	fraud	اِحْتِيال
875	fraudulence	اِحْتِيال
876	fraudulent	اِحْتِيال، مُزَوَّر، مُحْتال
877	fraudulently	شَكْل اِحْتِيال، نَحْو اِحْتِيال، طَرِيقَة اِحْتِيال، صُورَة اِحْتِيال
878	frivolous	تافِه، سَطْحِيّ
879	frivolously	طَرِيقَة سَطْحِيّ، نَحْو سَطْحِيّ
880	frustrate	حَبَط، ثَبَط
881	frustrated	حَبَط، ثَبَط، مُحْبِط
882	frustrates	حَبَط، ثَبَط
883	frustrating	حَبَط، ثَبَط، مُحْبِط
884	frustratingly	شَكْل مُحْبِط، نَحْو مُحْبِط، صُورَة مُحْبِط، طَرِيقَة مُحْبِط
885	frustration	إِحْباط
886	fugitives	هارِب، فارّ
887	gratuitous	بِلا داعِي، بِلا مُبَرِّر، بِلا سَبَب، غَيْر مُبَرِّر
888	gratuitously	شَكْل غَيْر مُبَرِّر، نَحْو غَيْر مُبَرِّر، صُورَة غَيْر مُبَرِّر، طَرِيقَة غَيْر مُبَرِّر
889	grievance	شَكْوَى، تَظَلُّم
890	grossly	شَكْل جَسِيم، نَحْو جَسِيم، شَكْل فادِح، نَحْو فادِح
891	groundless	لَيس مُبَرِّر، غَيْر مُبَرِّر، عار مِن صِحَّة، لا أَساس لِ، باطِل، بِلا أَساس
892	guilty	مُذْنِب، مُتَوَرِّط
893	halt	تَعَطَّل، تَوَقَّف، مُتَعَطِّل، مُتَوَقِّف
894	halted	تَعَطَّل، تَوَقَّف، مُتَعَطِّل، مُتَوَقِّف
895	hamper	كَبَح، أَعاق، عَرْقَل
896	hampered	كَبَح، أَعاق، عَرْقَل
897	hampering	كَبَح، أَعاق، عَرْقَل، عَرْقَلَة
898	harass	ضايَق، أَزْعَج، تَحَرَّش
899	harassed	ضايَق، أَزْعَج، تَحَرَّش، مُضايَقَة
900	harassing	ضايَق، أَزْعَج، تَحَرَّش، مُضايَقَة
901	harassment	مُضايَقَة، تَحَرُّش
902	hardship	مُعاناة، ضائِقَة
903	harm	ضَرّ، آذَى، ضَرَر، أَذَى
904	harmed	ضَرّ، آذَى، مُتَضَرِّر
905	harmful	ضارّ، مُضِرّ، مُؤْذِي
906	harmfully	شَكْل ضارّ، نَحْو ضارّ، صُورَة ضارّ، طَرِيقَة ضارّ، شَكْل مُؤْذِي، نَحْو مُؤْذِي، صُورَة مُؤْذِي، طَرِيقَة مُؤْذِي
907	harming	ضَرّ، آذَى، ضَرَر، أَذَى

No.	English Word	Arabic Translation
908	harsh	فَظّ، قَسْوَة، قاسِي، شِدَّة
909	harsher	أَقْسَى، أَشَدّ
910	harshest	أَشَدّ، أَكْثَر شِدَّة، أَقْسَى، أَكْثَر قَسْوَة
911	harshly	شِدَّة، قَسْوَة
912	harshness	شِدَّة، قَسْوَة، فَظاظَة، خُشُونَة
913	hazard	خاطَر، جازَف، خَطَر
914	hazardous	خَطِير
915	hinder	عَرْقَل، أعاق
916	hindered	عَرْقَل، أعاق
917	hindering	عَرْقَل، أعاق، أعاق، عَرْقَلَة
918	hinders	عَرْقَل، أعاق
919	hindrance	إعاقَة، عَرْقَلَة
920	hostile	عَدّاء، مُعاد
921	hostility	عَداء
922	hurt	ضَرّ، آذَى، ضَرَر، أَذَى
923	hurting	ضَرّ، آذَى، ضَرَر، أَذَى
924	idle	تَكاسَل، تَكاسَل، خامِل، مُعَطَّل، مُتَعَطِّل
925	idled	تَكاسَل، خامِل، مُعَطَّل
926	idling	تَكاسَل، تَكاسَل، خامِل، مُعَطَّل، خُمُول، تَباطُؤ
927	ignore	أَهْمَل، تَجاهَل، أَغْفَل
928	ignored	أَهْمَل، تَجاهَل، أَغْفَل، مُهْمَل
929	ignores	أَهْمَل، تَجاهَل، أَغْفَل
930	ignoring	أَهْمَل، تَجاهَل، أَغْفَل، مُهْمَل
931	ill	مُعْتَلّ
932	illegal	غَيْر قانُونِيّ، مَحْظُور، مُخالِف قانُون
933	illegality	عَدَم مَشْرُوعِيَّة، عَدَم شَرْعِيَّة، تَجاوُز قانُون، اِنْتِهاك قانُون
934	illegally	شَكْل غَيْر قانُونِيّ، نَحْو غَيْر قانُونِيّ، صُورَة غَيْر قانُونِيّ، طَرِيقَة غَيْر قانُونِيّ، غَيْر قانُونِيّ، صُورَة غَيْر شَرْعِيّ، شَكْل مُخالِف قانُون، نَحْو مُخالِف قانُون
935	illegible	مُبْهَم، غَيْر مَقْرُوء، صَعْب قِراءَة
936	illicit	مَحْظُور، غَيْر قانُونِيّ، غَيْر مَشْرُوع
937	illicitly	شَكْل غَيْر قانُونِيّ، نَحْو غَيْر قانُونِيّ، صُورَة غَيْر قانُونِيّ، طَرِيقَة غَيْر قانُونِيّ، شَكْل مُخالِف قانُون، نَحْو مُخالِف قانُون
938	illiquid	غَيْر قابِل تَداوُل
939	illiquidity	اِنْخِفاض سُيُولَة، نَقْص سُيُولَة، عَدَم كِفايَة سُيُولَة، شَحّ سُيُولَة، عَدَم سُيُولَة
940	imbalance	اِخْتِلال تَوازُن، عَدَم تَوازُن، اِنْعِدام تَوازُن
941	immature	غَيْر ناضِج، عَدَم نَضْج
942	immoral	غَيْر أَخْلاقِيّ، مُنافِي خُلُق، لاأَخْلاقِيّ، غَيْر أَخْلاقِيّ
943	impair	أَضْعَف، تَلِف
944	impaired	أَضْعَف، تَلِف، ضَرّ، مُتَضَرِّر، ضَعِيف
945	impairing	أَضْعَف، تَلِف، ضَرّ، مُتَضَرِّر، ضَعِيف، اِعْتِلال، ضُعْف، تَدَهْوُر
946	impairment	اِعْتِلال، ضُعْف، تَدَهْوُر
947	impairs	أَضْعَف، تَلِف، ضَرّ
948	impasse	مَأْزِق، طَرِيق مَسْدُود
949	impede	أعاق، عَرْقَل
950	impeded	أعاق، عَرْقَل، عائِق، مُعَرْقِل
951	impedes	أعاق، عَرْقَل
952	impediment	عائِق
953	impeding	أعاق، عَرْقَل، عائِق، مُعَرْقِل
954	impending	وَشِيك
955	imperative	مُلِحّ، حَتْمِيّ
956	imperfection	عَيْب، نَقْص
957	imperil	عَرَّض

No.	English Word	Arabic Translation
958	impermissible	غَيْر مَسْمُوح، غَيْر مَقْبُول
959	implicate	أَوْرَط
960	implicated	أَوْرَط، مُتَوَرِّط
961	implicates	أَوْرَط
962	implicating	أَوْرَط، مُتَوَرِّط
963	impossibility	اِسْتِحالَة
964	impossible	مُسْتَحِيل
965	impound	حَجَز، صادَر
966	impounded	حَجَز، صادَر، مُحْتَجَز، مَصادَر
967	impounding	حَجَز، صادَر، مُحْتَجَز، مَصادَر
968	impounds	حَجَز، صادَر
969	impracticable	غَيْر عَمَلِيّ، لَيس عَمَلِيّ، غَيْر واقِعِيّ، لَيس واقِعِيّ، لا أَمْكَن تَطْبِيق، غَيْر قابِل تَطْبِيق، غَيْر قابِل تَنْفِيذ
970	impractical	غَيْر عَمَلِيّ، لَيس عَمَلِيّ، غَيْر واقِعِيّ، لَيس واقِعِيّ
971	impracticality	عَدَم واقِعِيَّة
972	imprisonment	سَجْنَة، اِعْتِقال، إِيقاف أَمْنِيّ
973	improper	غَيْر مَلام، غَيْر لائِق، غَيْر مُناسِب
974	improperly	شَكْل غَيْر مَلام، نَحْو غَيْر مَلام، شَكْل غَيْر لائِق، نَحْو غَيْر مَلام
975	impropriety	بَذاء
976	imprudent	طائِش، مُتَهَوِّر
977	imprudently	شَكْل طائِش، نَحْو طائِش، شَكْل مُتَهَوِّر، نَحْو مُتَهَوِّر
978	inability	عَجْز، عَدَم قُدْرَة
979	inaccessible	غَيْر مُتاح، تَعَذَّر وُصُول إِلَى
980	inaccuracy	عَدَم دِقَّة
981	inaccurate	غَيْر دَقِيق
982	inaccurately	شَكْل غَيْر دَقِيق، نَحْو غَيْر دَقِيق، صُورَة غَيْر دَقِيقَة، طَرِيقَة غَيْر دَقِيقَة
983	inaction	تَراخِي، كَسَل
984	inactivate	عَطَّل
985	inactivated	عَطَّل، مُعَطَّل
986	inactivates	عَطَّل
987	inactivating	عَطَّل
988	inactivation	تَعَطَّل
989	inactivity	تَعَطَّل
990	inadequacy	قُصُور، نَقْص، عَدَم كِفايَة
991	inadequate	قاصِر، غَيْر كافِي، غَيْر مُؤَهَّل
992	inadequately	شَكْل غَيْر مَلام، نَحْو غَيْر مَلام، شَكْل غَيْر كافِي، نَحْو غَيْر كافِي
993	inadvertent	غافَل، غَيْر مَقْصُود، غَيْر مُتَعَمَّد، خَطَأ غَيْر مَقْصُود، عَن غَيْر قَصَد
994	inadvertently	غَيْر مَقْصُود، شَكْل غَيْر مَقْصُود، شَكْل غَيْر مُتَعَمَّد، عَن غَيْر قَصَد، دُون قَصَد
995	inadvisability	عَدَم مُلاءَمَة، عَدَم جَدارَة نَصْح
996	inadvisable	غَيْر مُوصَى بِ، غَيْر مَرْغُوب فِي، غَيْر مُسْتَحْسَن، غَيْر مُناسِب
997	inappropriate	غَيْر مَلام، غَيْر لائِق، غَيْر مُناسِب
998	inappropriately	شَكْل غَيْر مَلام، شَكْل غَيْر لائِق، شَكْل غَيْر مُناسِب، طَرِيقَة غَيْر مَقْبُول، صُورَة غَيْر مُناسَبَة
999	inattention	عَدَم اِنْتِباه، عَدَم تَرْكِيز، عَدَم اِكْتِراث
1000	incapable	عاجِز، مَحْدُود قُدْرَة
1001	incapacitated	عاجِز، غَيْر قادِر
1002	incapacity	عَجْز، عَدَم قُدْرَة
1003	incarcerate	سَجَن، اِحْتَجَز
1004	incarcerated	سَجَن، اِحْتَجَز، سَجِين، مُحْتَجَز
1005	incarcerates	سَجَن، اِحْتَجَز
1006	incarcerating	سَجَن، اِحْتَجَز، سَجِين، مُحْتَجَز
1007	incarceration	سِجْن، حَجْز

No.	English Word	Arabic Translation
1008	incidence	حادِث
1009	incident	حادِث
1010	incompatibility	عَدَم اِنْسِجام، عَدَم تَوافُق، تَعارُض، تَضارُب
1011	incompatible	مُتَضارِب، مُتَعارِض، غَيْر مُنْسَجِم، لَيس مُنْسَجِم
1012	incompetence	قَصْر أداء، عَدَم كَفاءَة
1013	incompetency	قُصُور، عَدَم كَفاءَة
1014	incompetent	عاجِز، عَدِيم كَفاءَة، غَيْر مُؤَهَّل، غَيْر كُفُوء
1015	incompetently	شَكْل غَيْر مُكْتَمَل، شَكْل غَيْر كُفُوء، شَكْل غَيْر ماهِر، بِلا كَفاءَة
1016	incomplete	ناقِص، غَيْر مُكْتَمَل
1017	incompletely	شَكْل غَيْر مُكْتَمَل، شَكْل مَنْقُوص، شَكْل ناقِص، شَكْل غَيْر كامِل
1018	incompleteness	نَقْص
1019	inconclusive	غَيْر حاسِم، مُتَرَدِّد، غَيْر مُؤَكِّد، غَيْر مُقْنِع، غَيْر قاطِع
1020	inconsistency	عَدَم اِتِّساق، عَدَم تَناسُق، تَناقُض، عَدَم ثَبات
1021	inconsistent	غَيْر مُتَّسِق، غَيْر ثابِت
1022	inconsistently	شَكْل مُتَناقِض، نَحْو مُتَناقِض، شَكْل غَيْر ثابِت، نَحْو غَيْر ثابِت، شَكْل غَيْر مُتَّسِق، نَحْو غَيْر مُتَّسِق، شَكْل مُتَضارِب، نَحْو مُتَضارِب
1023	inconvenience	مَشَقَّة، عَدَم راحَة
1024	inconvenient	مُتْعِب، غَيْر مُرِيح
1025	incorrect	خاطِئ، مَغْلُوط، غَيْر صَحِيح
1026	incorrectly	شَكْل خاطِئ، نَحْو خاطِئ، شَكْل غَيْر دَقِيق، نَحْو غَيْر دَقِيق، شَكْل مَغْلُوط، نَحْو مَغْلُوط، شَكْل غَيْر صَحِيح، نَحْو غَيْر صَحِيح
1027	incorrectness	عَدَم صِحَّة
1028	indecency	وَقاحَة، بَذاء
1029	indecent	وَقِح، بَذِيء
1030	indefeasible	لا أَمْكَن دَحْض، غَيْر قابِل بَطَل، غَيْر قابِل إِلْغاء، غَيْر قابِل نَقْض
1031	indefeasibly	غَيْر قابِل بَطَل، لا أَمْكَن دَحْض، لا أَمْكَن إِلْغاء، لا أَمْكَن حَمَل، غَيْر قابِل نَقْض، غَيْر قابِل إِلْغاء
1032	indict	اِتَّهَم، قاضَى، وَجَّه اِتِّهام
1033	indictable	عُرْضَة مُقاضاة، عُرْضَة اِتِّهام، مُسْتَوْجِب مُلاحَقَة قَضائِيّ
1034	indicted	مُتَّهَم
1035	indicting	مُقاضاة
1036	indictment	لائِحَة اِتِّهام، دَعْوَى قَضائِيّ، إدانَة، مُقاضاة
1037	ineffective	عَدِيم فائِدَة، غَيْر مَجْد، غَيْر فَعّال، عَدِيم جَداء
1038	ineffectively	شَكْل غَيْر فَعّال، نَحْو غَيْر فَعّال، شَكْل غَيْر مَجْد، نَحْو غَيْر مَجْدِي
1039	ineffectiveness	عَدَم جَداء، عَدَم فَعّالِيَّة، عَدِيم فائِدَة، عَدَم كَفاءَة
1040	inefficiency	عَدَم فَعّالِيَّة، عَدَم كَفاءَة، قُصُور
1041	inefficient	غَيْر كُفُوء، غَيْر فَعّال
1042	inefficiently	شَكْل غَيْر كُفُوء، شَكْل غَيْر فَعّال، نَحْو غَيْر فَعّال
1043	ineligibility	عَدَم أَهْلِيَّة، عَدَم جَدارَة، غَيْر مُؤَهَّل، عَدَم اِسْتِحْقاق
1044	ineligible	عَدِيم أَهْلِيَّة، غَيْر مُؤَهَّل، عَدِيم جَدارَة
1045	inequitable	مُجْحِف، جائِر، غَيْر مُنْصِف
1046	inequitably	شَكْل غَيْر عادِل، نَحْو غَيْر عادِل، شَكْل ظالِم، نَحْو ظالِم، شَكْل جائِر، نَحْو جائِر، شَكْل غَيْر مُنْصِف، نَحْو غَيْر مُنْصِف
1047	inequity	إِجْحاف، عَدَم مُساواة
1048	inevitable	حَتْمِيّ
1049	inexperience	قِلَّة خِبْرَة، عَدَم خِبْرَة
1050	inexperienced	قَلِيل خِبْرَة، غَيْر مُتَمَرِّس، عَدِيم خِبْرَة
1051	inferior	رَدِيء، دُون مُسْتَوَى
1052	inflicted	أَصاب
1053	infraction	خَرْق، مُخالَفَة، اِنْتِهاك
1054	infringe	اِنْتَهَك، خَرَق، خَرَق
1055	infringed	اِنْتَهَك، خَرَق، مُنْتَهَك، خَرَق

No.	English Word	Arabic Translation
1056	infringement	اِنْتِهاك، تَعَدّي
1057	infringes	اِنْتَهَك، خَرَق، خَرَق
1058	infringing	اِنْتِهاك، تَعَدّي
1059	inhibited	ثَبط، كَبَت، مُثَبَّط
1060	inimical	عَدّاء، مُعادِي
1061	injunction	أَمْر قَضائِيّ، إِنْذار قَضائِيّ
1062	injure	جَرَح، آذَى، أَصاب
1063	injured	جَرَح، آذَى، أَصاب
1064	injures	جَرَح، آذَى، أَصاب
1065	injuring	جَرَح، آذَى، أَصاب، مَجْرُوح، مُصاب، إِصابَة
1066	injurious	ضارّ، مُضِرّ، مُؤْذِي
1067	injury	أَذَى، ضَرَر، إِصابَة
1068	inordinate	مُبالَغ فِي، مُغالِي، مُفْرِط
1069	inordinately	شَكْل مُفْرِط، نَحْو مُفْرِط، صُورَة مُفْرِط
1070	inquiry	تَحَرّي، اِسْتِقْصاء، اِسْتِفْسار
1071	insecure	قَلَق، غَيْر مُسْتَقِرّ، غَيْر آمِن
1072	insensitive	مُتَبَلِّد، لَيس مُبالِي، غَيْر مُبالِي، لا مُبالِي
1073	insolvency	عَجْز عَن سَداد، إِعْسار، إِفْلاس
1074	insolvent	عاجِز عَن دَفْع، مُفْلِس، مُعْسِر
1075	instability	تَقَلُّب، اِنْعِدام اِسْتِقْرار، عَدَم اِسْتِقْرار، اِضْطِراب
1076	insubordination	تَمَرُّد، عِصْيان، تَجاوُز أَمْر
1077	insufficiency	قُصُور، عَدَم كِفايَة
1078	insufficient	ضَئِيل، غَيْر كافِي
1079	insufficiently	شَكْل غَيْر مُكْتَمَل، نَحْو غَيْر مُكْتَمَل، شَكْل ناقِص، شَكْل غَيْر مَلام، نَحْو غَيْر مَلام، شَكْل غَيْر كافِي، نَحْو غَيْر كافِي
1080	insurrection	تَمَرُّد
1081	intentional	مُتَعَمَّد
1082	interfere	تَدَخَّل، تَعارَض، تَصادَم
1083	interfered	تَدَخَّل، تَعارَض، تَصادَم، مُتَعارِض، مُتَدَخِّل
1084	interference	تَدَخُّل، تَعارُض، تَصادُم
1085	interferes	تَدَخَّل، تَعارَض، تَصادَم
1086	interfering	تَدَخُّل، تَعارُض، تَصادُم
1087	intermittent	مُتَقَطِّع
1088	intermittently	عَلَى فَتْرَة مُتَقَطِّع، شَكْل غَيْر مُسْتَمِرّ، نَحْو غَيْر مُسْتَمِرّ، شَكْل مُتَقَطِّع، نَحْو مُتَقَطِّع
1089	interrupt	قَطَع، عاق، عَطَّل
1090	interrupted	قَطَع، عاق، عَطَّل، مُنْقَطِع، مَقْطُوع
1091	interrupting	قَطَع، عاق، عَطَّل، مُنْقَطِع، مَقْطُوع، اِنْقِطاع، إِعاقَة، تَعَطُّل
1092	interruption	اِنْقِطاع، إِعاقَة، تَعَطُّل
1093	intimidation	تَهْدِيد، تَرْهِيب
1094	intrusion	اِخْتِراق، تَسَرُّب، اِقْتِحام
1095	invalid	باطِل، لاغِي، غَيْر قانُونِيّ، غَيْر صَحِيح
1096	invalidate	بَطَل، عَطَّل
1097	invalidated	بَطَل، عَطَّل، مُعَطَّل
1098	invalidates	بَطَل، عَطَّل
1099	invalidating	بَطَل، عَطَّل
1100	invalidation	إِبْطال
1101	invalidity	بطلان
1102	investigate	تَحَرَّى، تَقَصَّى، اِسْتَقْصَى
1103	investigated	تَحَرَّى، تَقَصَّى، اِسْتَقْصَى
1104	investigates	تَحَرَّى، تَقَصَّى، اِسْتَقْصَى
1105	investigating	تَحَرَّى، تَقَصَّى، اِسْتَقْصَى
1106	investigation	تَحَرّي، اِسْتِقْصاء

No.	English Word	Arabic Translation
1107	involuntarily	شَكْل إِلْزامِيّ، نَحْو إِلْزامِيّ
1108	involuntary	إِلْزامِيّ، قَسْرِيّ، إِجْبار
1109	irreconcilable	لا عَوَض، غَيْر قابِل تَعْوِيض
1110	irrecoverable	لا أَمْكَن تَعْوِيض، غَيْر قابِل اِسْتِرْداد، غَيْر قابِل اِسْتِعادَة، لا أَمْكَن اِسْتِرْداد، مُتَعَذِّر إِصْلاح
1111	irrecoverably	غَيْر قابِل اِسْتِرْداد، لا أَمْكَن اِسْتِرْداد
1112	irregular	غَيْر مُنْتَظِم، غَيْر مَأْلُوف، غَيْر عادِيّ
1113	irregularity	عَدَم اِنْتِظام
1114	irregularly	شَكْل غَيْر مُنْتَظِم، نَحْو غَيْر مُنْتَظِم، شَكْل لَيس مُنْتَظِم، نَحْو لَيس مُنْتَظِم
1115	irreparable	لا أَمْكَن إِصْلاح، مُتَعَذِّر إِصْلاح
1116	irreversible	لا رَجْعَة فِي، لا أَمْكَن تَغْيِير
1117	jeopardize	هَدَّد
1118	jeopardized	هَدَّد
1119	justifiable	مُبَرَّر، قابِل تَبْرِير
1120	kickback	رَشْوَة
1121	knowingly	نَحْو مُتَعَمَّد، شَكْل مُتَعَمَّد
1122	lack	شَحّ، قِلَّة، نَدْرَة
1123	lacked	اِفْتَقَر
1124	lacking	اِفْتَقَر، مُفْتَقِر، اِفْتِقار
1125	lackluster	شاحِب، باهِت
1126	lag	تَأَخُّر
1127	lagged	مُتَأَخِّر عَن
1128	lagging	تَأَخُّر
1129	lapse	اِنْقَضَى، هَفْوَة، تَراخِي، خَطَأ، سُقُوط
1130	lapsed	اِنْقَضَى
1131	lapsing	اِنْقَضَى
1132	laundering	غَسِيل مال، تَبْيِيض مال
1133	layoff	فَصْل، تَسْرِيح
1134	lie	كَذَّب، كِذْب
1135	limitation	قَصْر
1136	lingering	مُزْمِن
1137	liquidate	صَفَّى، سَيَّل
1138	liquidated	صَفَّى، سَيَّل
1139	liquidates	صَفَّى، سَيَّل
1140	liquidating	صَفَّى، سَيَّل
1141	liquidation	تَصْفِيَة
1142	liquidator	مَصَفّ
1143	litigant	مُدَّعَى، مُتَقاضَى، مُدَّعَى عَلَى
1144	litigate	تَخاصَم، قاضَى
1145	litigated	تَخاصَم، قاضَى، تَمّ مُقاضاة
1146	litigates	قاضَى
1147	litigating	قاضَى، مُتَقاضَى، مُدَّعَى عَلَى، تَقاضِي، مُقاضاة
1148	litigation	تَقاضِي، مُقاضاة
1149	lockout	إِغْلاق
1150	lose	خَسِر، أَفْقَد، ضاع، اِنْهَزَم، خَسارَة
1151	loses	خَسِر، أَفْقَد، ضاع، اِنْهَزَم
1152	losing	خَسِر، أَفْقَد، ضاع، اِنْهَزَم، خَسارَة
1153	loss	خَسارَة، هَزِيمَة
1154	lost	خَسِر، أَفْقَد، ضاع، اِنْهَزَم، خاسِر
1155	lying	كَذَّب، كاذِب، كِذْب
1156	malfeasance	سُوء سُلُوك، سُوء تَصَرُّف
1157	malfunction	تَعَطَّل
1158	malfunctioned	مُتَعَطِّل

No.	English Word	Arabic Translation
1159	malfunctioning	عَطّل، قَصْر
1160	malice	حِقْد، خَبَث
1161	malicious	حاقِد، خَبِيث، مُغْرِض
1162	maliciously	بِنْيَة إِلْحاق ضَرَر، سُوء نِيَّة، قَصْد إِلْحاق ضَرَر
1163	malpractice	إِهْمال مِهْنِيّ، سُوء اِسْتِخْدام سُلْطَة
1164	manipulate	تَلاعَب
1165	manipulated	تَلاعَب
1166	manipulates	تَلاعَب
1167	manipulating	تَلاعَب، تَلاعُب
1168	manipulation	تَلاعُب
1169	manipulative	تَلاعُب، اِسْتِغْلال
1170	markdown	تَقْلِيل قِيمَة، تَخْفِيض سِعْر، تَخْفِيض قِيمَة
1171	markdowns	تَقْلِيل قِيمَة، تَخْفِيض سِعْر، تَخْفِيض قِيمَة
1172	misapplication	إِساءَة تَطْبِيق، إِساءَة اِسْتِعْمال
1173	misapplied	أَساء تَطْبِيق، أَساء اِسْتِعْمال، أَخْطَأ فِي تَطْبِيق، إِساءَة تَطْبِيق، إِساءَة اِسْتِعْمال
1174	misapplies	أَساء تَطْبِيق، أَساء اِسْتِعْمال، أَخْطَأ فِي تَطْبِيق
1175	misapply	أَساء اِسْتِعْمال، أَساء تَطْبِيق
1176	misapplying	أَساء اِسْتِعْمال، أَساء تَطْبِيق، إِساءَة تَطْبِيق، إِساءَة اِسْتِعْمال
1177	misappropriate	اِخْتَلَس
1178	misappropriated	اِخْتَلَس، مُخْتَلَس
1179	misappropriates	اِخْتَلَس
1180	misappropriating	اِخْتَلَس، مُخْتَلَس، اِخْتِلاس
1181	misappropriation	اِخْتِلاس
1182	misbranded	غِشّ، ضَلّل
1183	miscalculate	أَخْطَأ فِي حِساب، أَخْطَأ فِي تَقْدِير
1184	miscalculated	أَخْطَأ فِي حِساب، أَخْطَأ فِي تَقْدِير
1185	miscalculates	أَخْطَأ فِي حِساب، أَخْطَأ فِي تَقْدِير
1186	miscalculating	أَخْطَأ فِي حِساب، أَخْطَأ فِي تَقْدِير
1187	miscalculation	حِساب غَيْر دَقِيق، سُوء تَقْدِير، تَقْدِير خاطِئ
1188	mischaracterization	تَفْسِير خاطِئ، تَوْصِيف خاطِئ
1189	mischief	أَذى، ضَرَر
1190	misclassification	تَرْتِيب غَيْر دَقِيق، تَرْتِيب خَطَأ، تَقْسِيم غَيْر صَحِيح، تَصْنِيف خاطِئ
1191	misclassified	خَطا فِي تَرْتِيب، أَخْطَأ فِي تَقْسِيم، أَخْطَأ فِي تَقْسِيم، أَخْطَأ فِي تَصْنِيف، مُصَنَّف خَطَأ
1192	misclassify	خَطا فِي تَرْتِيب، أَخْطَأ فِي تَقْسِيم، أَخْطَأ فِي تَقْسِيم، أَخْطَأ فِي تَصْنِيف
1193	miscommunication	سُوء فَهْم، سُوء اِتِّصال، خَلَل فِي تَواصُل، سُوء تَفاهُم
1194	misconduct	سُوء سُلُوك، إِساءَة سُلُوك
1195	misdated	مُؤَرَّخ شَكْل خاطِئ
1196	misdemeanor	جُنْحَة
1197	misdirected	ضَلّل، سُوء تَوْجِيه
1198	mishandle	أَساء مُعامَلَة، أَساء إِدارَة، أَساء تَصَرُّف، إِساءَة مُعامَلَة، إِساءَة إِدارَة، إِساءَة تَصَرُّف، إِساءَة تَعامُل، سُوء تَعامُل، سُوء تَصَرُّف، تَدْبِير خاطِئ، تَعامُل سَيِّء
1199	mishandled	أَساء مُعامَلَة، أَساء إِدارَة، أَساء تَصَرُّف، مُعامَلَة سَيِّء
1200	mishandles	أَساء مُعامَلَة، أَساء إِدارَة، أَساء تَصَرُّف
1201	mishandling	أَساء مُعامَلَة، أَساء إِدارَة، أَساء تَصَرُّف، مُعامَلَة سَيِّء، إِساءَة مُعامَلَة، إِساءَة إِدارَة، إِساءَة تَصَرُّف، إِساءَة تَعامُل، سُوء تَعامُل، سُوء تَصَرُّف، تَدْبِير خاطِئ، تَعامُل سَيِّء
1202	misinform	ضَلّل، خَدَع
1203	misinformation	بَيان مَغْلُوط، بَيان مُضَلِّل، بَيان خاطِئ، مَعْلُومَة مَغْلُوط، مَعْلُومَة مُضَلِّل، مَعْلُومَة خاطِئ
1204	misinformed	ضَلّل، خَدَع، مُضَلِّل
1205	misinforming	ضَلّل، خَدَع، بَيان مَغْلُوط، بَيان مُضَلِّل، بَيان خاطِئ، مَعْلُومَة مَغْلُوط، مَعْلُومَة مُضَلِّل، مَعْلُومَة خاطِئ
1206	misinforms	ضَلّل، خَدَع
1207	misinterpret	أَساء تَفْسِير، أَساء فَهْم

No.	English Word	Arabic Translation
1208	misinterpretation	إِساءَة تَفْسِير، سُوء فَهْم، إِساءَة تَفْسِير، إِساءَة فَهْم، تَأْوِيل خاطِئ، تَفْسِير خاطِئ
1209	misinterpreted	أَساء تَفْسِير، أَساء فَهْم
1210	misinterpreting	أَساء تَفْسِير، أَساء فَهْم، إِساءَة تَفْسِير، إِساءَة فَهْم، تَأْوِيل خاطِئ، تَفْسِير خاطِئ
1211	misinterprets	أَساء تَفْسِير، أَساء فَهْم
1212	misjudge	أَخْطَأَ فِي حُكْم، أَساء حُكْم، أَساء تَقْدِير، حَكَم شَكْل خاطِئ، قَدَّر شَكْل خاطِئ
1213	misjudged	أَخْطَأَ فِي حُكْم، أَساء حُكْم، أَساء تَقْدِير، حَكَم شَكْل خاطِئ، قَدَّر شَكْل خاطِئ
1214	misjudges	أَخْطَأَ فِي حُكْم، أَساء حُكْم، أَساء تَقْدِير، حَكَم شَكْل خاطِئ، قَدَّر شَكْل خاطِئ
1215	misjudging	أَخْطَأَ فِي حُكْم، أَساء حُكْم، أَساء تَقْدِير، حَكَم شَكْل خاطِئ، قَدَّر شَكْل خاطِئ
1216	misjudgment	،إِساءَة حُكْم، إِساءَة تَقْدِير، سُوء حُكْم، سُوء تَقْدِير، إِساءَة تَقْدِير، حُكْم خاطِئ، سُوء حُكْم تَقْدِير خاطِئ
1217	mislabel	أَساء تَسْمِيَة
1218	mislabeled	أَساء تَسْمِيَة، مُصَنَّف شَكْل خَطَأ، مَوْصُوف شَكْل خاطِئ، خَطَأ فِي تَصْنِيف، تَوْصِيف خاطِئ
1219	mislabeling	أَساء تَسْمِيَة، مُصَنَّف شَكْل خَطَأ، مَوْصُوف شَكْل خاطِئ، خَطَأ فِي تَصْنِيف، تَوْصِيف خاطِئ
1220	mislabelled	تَسْمِيَة خاطِئ، مُصَنَّف خَطَأ، مُسَمَّى خَطَأ، مَوْصُوف شَكْل خاطِئ، أَساء تَسْمِيَة، تَصْنِيف خاطِئ
1221	mislabels	أَساء تَسْمِيَة
1222	mislead	ضَلَّل، خَدَع، ضَلَّل، سُوء تَعامُل
1223	misleading	ضَلَّل، خَدَع، ضَلَّل، سُوء تَعامُل
1224	misleadingly	شَكْل مُضَلِّل، نَحْو مُضَلِّل، شَكْل خادِع، نَحْو خادِع
1225	misleads	ضَلَّل، خَدَع، ضَلَّل
1226	misled	ضَلَّل، خَدَع، ضَلَّل
1227	mismanage	خَفَق فِي إِدارَة، أَساء إِدارَة، أَساء تَدْبِير، خَفَق فِي إِدارَة
1228	mismanaged	خَفَق فِي إِدارَة، أَساء إِدارَة، أَساء تَدْبِير، خَفَق فِي إِدارَة، سُوء إِدارَة
1229	mismanagement	سُوء إِدارَة، فَشَل إِدارِيّ، سُوء تَدْبِير، تَقْصِير إِدارِيّ، إِهْمال إِدارِيّ
1230	mismanages	خَفَق فِي إِدارَة، أَساء إِدارَة، أَساء تَدْبِير، خَفَق فِي إِدارَة
1231	mismanaging	خَفَق فِي إِدارَة، أَساء إِدارَة، أَساء تَدْبِير، خَفَق فِي إِدارَة، سُوء إِدارَة، فَشَل إِدارِيّ، سُوء تَدْبِير، تَقْصِير إِدارِيّ، إِهْمال إِدارِيّ
1232	mismatch	غَيْر مُتَطابِق
1233	mismatched	غَيْر مُتَطابِق
1234	mismatching	غَيْر مُتَطابِق
1235	misplaced	ضاع، مَفْقُود، ضائِع
1236	misprice	،أَخْطَأَ فِي تَسْعِير، سَعَر شَكْل خاطِئ، خَلَل فِي تَسْعِير، تَسْعِير خاطِئ، خَطَأ فِي تَسْعِير تَسْعِير خاطِئ، سُوء تَسْعِير
1237	mispricing	،أَخْطَأَ فِي تَسْعِير، سَعَر شَكْل خاطِئ، خَلَل فِي تَسْعِير، تَسْعِير خاطِئ، خَطَأ فِي تَسْعِير تَسْعِير خاطِئ، سُوء تَسْعِير
1238	mispricings	أَخْطَأَ فِي تَسْعِير، سَعَر شَكْل خاطِئ
1239	misrepresent	حَرَّف، خَدَع، ضَلَّل
1240	misrepresentation	تَحْرِيف، خِداع، تَضْلِيل
1241	misrepresented	حَرَّف، خَدَع، ضَلَّل، مَغْلُوط، مُحَرَّف
1242	misrepresenting	حَرَّف، خَدَع، ضَلَّل، مَغْلُوط، مُحَرَّف، تَحْرِيف، خِداع، تَضْلِيل
1243	misrepresents	حَرَّف، خَدَع، ضَلَّل
1244	miss	فات
1245	missed	ضائِع، أَخْطَأَ، فائِت
1246	misstate	شَوَّه، حَرَّف
1247	misstated	شَوَّه، حَرَّف، مُحَرَّف، مَشَى
1248	misstatement	تَصْرِيح غَيْر صَحِيح، تَصْرِيح خاطِئ، بَيان كاذِب، إِعْلان كاذِب، إِفادَة غَيْر صَحِيح
1249	misstates	شَوَّه، حَرَّف، شَوَّه، صَرَّح شَكْل خاطِئ، أَعْلَن شَكْل خاطِئ
1250	misstating	شَوَّه، حَرَّف، مُحَرَّف، مَشَى
1251	misstep	تَعَثَّر، خَطَأ، إِخْفاق، غَلْطَة
1252	mistake	أَخْطَأَ، غَلِط، خَطَأ، غَلْطَة، سُوء فَهْم

No.	English Word	Arabic Translation
1253	mistaken	أَخْطَأَ، غَلِط، مُخْطِئ، خاطِئ، مَغْلوط
1254	mistakenly	شَكْل خاطِئ، نَحْو خاطِئ، شَكْل مُخْطِئ، نَحْو مُخْطِئ، عَن طَرِيق خَطَأ
1255	mistaking	أَخْطَأَ، غَلِط، مُخْطِئ، خاطِئ، مَغْلوط
1256	mistrial	مُحاكَمَة مُلْغَى، مُحاكَمَة باطِل
1257	misunderstand	أَساء فَهْم، أَخْطَأَ فَهْم
1258	misunderstanding	أَساء فَهْم، أَخْطَأَ فَهْم، سُوء فَهْم، سُوء فِي فَهْم
1259	misunderstood	أَساء فَهْم، أَخْطَأَ فَهْم، سُوء فَهْم، سُوء فِي فَهْم
1260	misuse	أساء اِسْتِعْمال، أساء اِسْتِخْدام، اِسْتِغْلال خاطِئ، إساءَة اِسْتِعْمال، إساءَة اِسْتِخْدام، سُوء اِسْتِعْمال، سُوء اِسْتِخْدام
1261	misused	أساء اِسْتِعْمال، أساء اِسْتِخْدام
1262	misusing	أساء اِسْتِعْمال، أساء اِسْتِخْدام، اِسْتِغْلال خاطِئ، إساءَة اِسْتِعْمال، إساءَة اِسْتِخْدام، سُوء اِسْتِعْمال، سُوء اِسْتِخْدام
1263	monopolists	مُحْتَكِر
1264	monopolistic	مُحْتَكِر، اِحْتِكار
1265	monopolization	اِحْتِكار
1266	monopolize	اِحْتَكَر
1267	monopolized	اِحْتَكَر، مُحْتَكِر
1268	monopolizes	اِحْتَكَر
1269	monopolizing	اِحْتَكَر، اِحْتِكار
1270	monopoly	اِحْتِكار
1271	moratorium	حَظْر، تَجْمِيد، فَرْض حَظْر
1272	mothballed	جَمَّد، عَطَّل
1273	mothballing	جَمَّد، عَطَّل، مُتَجَمِّد، مُتَعَطِّل، تَجْمِيد، تَعَطَّل
1274	negative	سَلْبِيّ
1275	negatively	شَكْل سَلْبِيّ، نَحْو سَلْبِيّ
1276	neglect	أَغْفَل، أَهْمَل، تَهاوَن
1277	neglected	أَغْفَل، أَهْمَل، مُتَهاوِن، مُهْمَل
1278	neglectful	مُهْمَل، لا مُبالِي، غَيْر مُبالِي
1279	neglecting	أَغْفَل، أَهْمَل، تَهاوَن
1280	negligence	إِهْمال، تَقْصِير، تَهاوُن
1281	negligent	مُهْمَل، مُتَهاوِن، غَيْر مُبالِي
1282	negligently	شَكْل مُتَهاوِن، نَحْو مُتَهاوِن، شَكْل غَيْر مُبالِي، نَحْو غَيْر مُبالِي
1283	noncompetitive	خال مِن مُنافَسَة، غَيْر تَنافُس، اِحْتِكار
1284	noncompliance	عَدَم اِلْتِزام، عَدَم مُطابَقَة، عَدَم اِمْتِثال
1285	noncompliant	غَيْر مُطَابِقٌ
1286	noncomplying	غَيْر مُطَابِقٌ
1287	nonconforming	غَيْر مُطَابِقٌ، عَدَم تَوافُق
1288	nonconformity	عَدَم مُطابَقَة، عَدَم تَوافُق
1289	nondisclosure	حَجْب مَعْلُومَة، عَدَم إِفْصاح
1290	nonfunctional	مُتَعَطِّل، مُعَطَّل، عاطِل، خارِج خِدْمَة
1291	nonpayment	تَقْصِير فِي سَداد، تَخَلُّف عَن دَفْع، عَدَم دَفْع، عَدَم سَداد
1292	nonperformance	عَدَم اِسْتِجابَة، فَشَل فِي أَداء، تَقْصِير فِي أَداء
1293	nonperforming	غَيْر فَعّال، مُتَعَثِّر، غَيْر مُثْمِر
1294	nonproducing	غَيْر مُنْتِج، غَيْر مُثْمِر، غَيْر مُفِيد
1295	nonproductive	غَيْر فَعّال، غَيْر مُرْبِح، غَيْر مُنْتِج، غَيْر مُثْمِر
1296	nonrecoverable	لا أَمْكَن اِسْتِعادَة، لا أَمْكَن تَحْصِيل، لا أَمْكَن اِسْتِرْجاع، غَيْر قابِل اِسْتِرْداد
1297	nonrenewal	عَدَم تَجْدِيد
1298	nuisance	أَذَى، إِزْعاج
1299	nullification	إِبْطال، نَقْض
1300	nullified	بَطَل، أَلْغَى، مُلْغَى
1301	nullifies	بَطَل، أَلْغَى
1302	nullify	بَطَل، أَلْغَى

No.	English Word	Arabic Translation
1303	nullifying	بَطَل، أَلْغَى، بَطَل، إِبْطال
1304	objected	اِعْتَرَض، رَفَض، مُعْتَرِض
1305	objecting	اِعْتَرَض، رَفَض، مُعْتَرِض، اِعْتِراض
1306	objection	اِعْتِراض، اِحْتِجاج
1307	objectionable	مَرْفُوض، غَيْر مَقْبُول
1308	objectionably	شَكْل مَرْفُوض، نَحْو مَرْفُوض، شَكْل غَيْر مَقْبُول، نَحْو غَيْر مَقْبُول
1309	obscene	فاحِش، دَنِيء، بَغِيض، بَذِيء
1310	obscenity	فُحْش، بَذاء
1311	obsolescence	تَقادُم
1312	obsolete	بائِد
1313	obstacle	عَقَبَة، عائِق
1314	obstruct	عَرْقَل، أعاق، حَجَب
1315	obstructed	عَرْقَل، أعاق، حَجَب، مَسْدُود
1316	obstructing	عَرْقَل، أعاق، حَجَب، عَرْقَلَة
1317	obstruction	عَرْقَلَة
1318	offence	إِساءَة، إِهانَة
1319	offend	أساء
1320	offended	أساء
1321	offender	مُسِيء، جانِي
1322	offending	أساء، مُسِيء، مُذْنِب
1323	offends	أساء
1324	omission	إِغْفال، إِهْمال، حَذْف
1325	omit	أَسْقَط، أَهْمَل، أَغْفَل، حَذَف
1326	omits	أَسْقَط، أَغْفَل، أَهْمَل، حَذَف
1327	omitted	أَسْقَط، أَغْفَل، أَهْمَل، حَذَف، مُهْمَل
1328	omitting	أَسْقَط، أَغْفَل، أَهْمَل، حَذَف، مُهْمَل، إِغْفال، إِهْمال، حَذْف
1329	onerous	شاقّ، مُرْهِق
1330	opportunistic	اِنْتِهازِيّ
1331	opportunistically	شَكْل اِنْتِهازِيّ، نَحْو اِنْتِهازِيّ
1332	oppose	اِعْتَرَض، مانَع
1333	opposed	اِعْتَرَض، مانَع، مُعارِض
1334	opposes	اِعْتَرَض، مانَع
1335	opposing	اِعْتَرَض، مانَع، مُعارِض
1336	opposition	مُعارِض
1337	outage	عَطْل، اِنْقِطاع
1338	outdated	مَهْجُور، قَدِيم
1339	outmoded	مَهْجُور
1340	overage	فائِض
1341	overbuild	تَجاوَز فِي بِناء، فَرَّط فِي إِنْشاء، بالَغ فِي بِناء، مُبالَغَة فِي بِناء، إِفْراط فِي بِناء
1342	overbuilding	تَجاوَز فِي بِناء، فَرَّط فِي إِنْشاء، بالَغ فِي بِناء، مُبالَغَة فِي بِناء، إِفْراط فِي بِناء
1343	overbuilds	تَجاوَز فِي بِناء، فَرَّط فِي إِنْشاء، بالَغ فِي بِناء
1344	overbuilt	مُبالَغَة فِي بِناء، تَجاوَز فِي بِناء، مُبالَغَة فِي بِناء
1345	overburden	أَثْقَل، عِبْء زائِد، مُثْقَّل
1346	overburdened	أَثْقَل، مُثْقَّل
1347	overburdening	أَثْقَل، عِبْء زائِد، مُثْقَّل، أَثْقال
1348	overcapacities	قُدْرَة زائِد، طاقَة زائِد، فائِض قُدْرَة، فائِض طاقَة
1349	overcapacity	قُدْرَة زائِد، طاقَة زائِد، فائِض قُدْرَة، فائِض طاقَة
1350	overcharge	بالَغ، غالَى، رَسْم زائِد
1351	overcharged	بالَغ، غالَى
1352	overcharging	مُغالاة
1353	overcome	تَصَدَّى، تَغَلَّب
1354	overcomes	تَصَدَّى، تَغَلَّب

No.	English Word	Arabic Translation
1355	overcoming	تَصَدَّى، تَغَلَّب
1356	overdue	تَأَخَّر سَداد، مَبْلَغ مُسْتَحِقّ، تَأَخَّر، مُتَأَخِّر
1357	overestimate	بالَغ، غالَى
1358	overestimated	مُبالَغ فِي، بالِغ، مُبالَغ فِي تَقْدِير
1359	overestimating	مُبالَغ فِي تَقْدِير، مُغالاة
1360	overestimation	مُبالَغَة، مُبالَغَة فِي تَقْدِير
1361	overload	أَثْقَل، عِبْء زائِد، تَحْمِيل زائِد، حُمُولَة زائِد، تَحْمِيل زائِد، زِيادَة تَحْمِيل
1362	overloaded	أَثْقَل
1363	overloading	أَثْقَل، عِبْء زائِد، تَحْمِيل زائِد، حُمُولَة زائِد، تَحْمِيل زائِد، زِيادَة تَحْمِيل
1364	overlook	تَجاهَل، تَغاضَى، أَغْفَل، تَجاهُل
1365	overlooked	تَجاهَل، تَغاضَى، أَغْفَل
1366	overlooking	تَجاهَل، تَغاضَى، أَغْفَل، تَجاهُل
1367	overpaid	دَفَع زِيادَة
1368	overpayment	دَفْع زائِد
1369	overproduced	فَرَّط فِي إِنْتاج، فائِض إِنْتاج
1370	overproduces	فَرَّط فِي إِنْتاج
1371	overproducing	إِنْتاج زائِد، إِفْراط فِي إِنْتاج
1372	overproduction	إِنْتاج مُفْرِط، فائِض إِنْتاج، إِنْتاج زائِد، أَخْفَى، حَجْب
1373	overrun	أَفاض عَن، إِعْتام، إِخْفاء
1374	overrunning	أَفاض عَن، غَطَّى، اِعْتَمّ، ظَلَّل
1375	overshadow	أَخْفَى، حَجَب
1376	overshadowed	أَخْفَى، حَجَب
1377	overshadowing	أَخْفَى، حَجَب
1378	overshadows	أَخْفَى، حَجَب
1379	overstate	بالَغ، غالَى
1380	overstated	بالَغ، مُغالِي بِ، مُبالَغ فِي
1381	overstatement	مُبالَغَة، تَهْوِيل
1382	overstates	بالَغ، غالَى
1383	overstating	مُبالَغَة
1384	oversupplied	فائِض عَرْض، فائِض فِي عَرْض، فائِض تَمْوِين
1385	oversupply	فائِض عَرْض، فائِض فِي عَرْض، فائِض تَمْوِين
1386	oversupplying	فائِض عَرْض، فائِض فِي عَرْض، فائِض تَمْوِين
1387	overtly	شَكْل عَلَنِيّ
1388	overturn	أَسْقَط، أَلْغَى، بَطَل، فَسَخ
1389	overturned	أَسْقَط، أَلْغَى، بَطَل، فَسَخ، مُلْغَى
1390	overturning	أَسْقَط، أَلْغَى، بَطَل، فَسَخ
1391	overvalue	بالَغ فِي تَقْيِيم، بالَغ فِي تَقْدِير، بالَغ فِي تَثْمِين، فَرَّط فِي تَقْيِيم، فَرَّط فِي تَقْيِيم، فَرَّط فِي تَثْمِين
1392	overvalued	بالَغ فِي تَقْيِيم، بالَغ فِي تَقْدِير، بالَغ فِي تَثْمِين، فَرَّط فِي تَقْيِيم، فَرَّط فِي تَقْيِيم، فَرَّط فِي تَثْمِين، مُبالَغ فِي قِيمَة، مُغالِي فِي تَقْدِير، مُفْرِط فِي تَقْيِيم، مُبالَغَة فِي قِيمَة
1393	overvaluing	بالَغ فِي تَقْيِيم، بالَغ فِي تَقْدِير، بالَغ فِي تَثْمِين، فَرَّط فِي تَقْيِيم، فَرَّط فِي تَقْيِيم، فَرَّط فِي تَثْمِين، مُبالَغ فِي قِيمَة، مُغالِي فِي تَقْدِير، مُفْرِط فِي تَقْيِيم، مُبالَغَة فِي قِيمَة
1394	panic	فَزَع، هَلَع، ذُعْر، اِرْتِباك
1395	penalize	عاقَب، غَرِم
1396	penalized	عاقَب، غَرِم، مُعاقِب
1397	penalizes	عاقَب، غَرِم
1398	penalizing	عاقَب، غَرِم، مُعاقَبَة
1399	penalty	عِقاب، غَرامَة، عُقُوبَة
1400	peril	خَطَر
1401	perjury	حَنِث، شَهادَة زُور، كِذْب تَحْتَ قِسْم، إِدْلاء شَهادَة كاذِب
1402	perpetrate	اِقْتَرَف، اِرْتَكَب
1403	perpetrated	اِقْتَرَف، اِرْتَكَب

No.	English Word	Arabic Translation
1404	perpetrates	اِقْتَرَف، اِرْتَكَب
1405	perpetrating	اِقْتَرَف، اِرْتَكَب
1406	perpetration	اِقْتِراف، اِرْتِكاب
1407	persist	أَلَحّ
1408	persisted	أَلَحّ
1409	persistence	إِلْحاح
1410	persistent	مُلِحّ
1411	persistently	شَكْل مُلِحّ، نَحْو مُلِحّ
1412	persisting	أَلَحّ
1413	persists	أَلَحّ
1414	pervasive	مُتَفَشِّي
1415	pervasively	نَحْو مُتَفَشِّي، شَكْل مُتَفَشِّي
1416	pervasiveness	تَفَشِّي
1417	petty	تافِه
1418	picket	اِحْتاج
1419	picketed	اِحْتاج، مُحْتَجّ
1420	picketing	اِحْتاج، مُحْتَجّ، اِحْتِجاج
1421	plaintiff	مُدَّعِي
1422	plea	اِلْتِماس، تَوَسُّل
1423	plead	اِلْتَمَس، تَوَسَّل
1424	pleaded	اِلْتَمَس، تَوَسَّل
1425	pleading	اِلْتَمَس، تَوَسَّل
1426	pleads	اِلْتَمَس، تَوَسَّل
1427	pled	اِلْتَمَس، تَوَسَّل
1428	poor	سُوء، فَقِير، رَدِيء
1429	poorly	شَكْل سَيِّء، نَحْو سَيِّء، شَكْل رَدِيء، نَحْو رَدِيء
1430	poses	أَرْبَك
1431	posing	أَرْبَك، إِرْباك
1432	postpone	أَجَّل، أَرْجَأ، عَلَّق
1433	postponed	أَجَّل، أَرْجَأ، عَلَّق، مُؤَخَّر، مُؤَجَّل
1434	postponement	تَأْجِيل
1435	postpones	أَجَّل، أَرْجَأ، عَلَّق
1436	postponing	أَجَّل، أَرْجَأ، عَلَّق، مُؤَخَّر، مُؤَجَّل، تَأْجِيل
1437	precipitated	تَعَجَّل، مُتَهَوِّر، مُتَعَجِّل
1438	precipitous	مُتَهَوِّر، مُتَعَجِّل
1439	precipitously	شَكْل مُتَعَجِّل، نَحْو مُتَعَجِّل
1440	preclude	أَعاق
1441	precluded	أَعاق
1442	precludes	أَعاق
1443	precluding	أَعاق
1444	predatory	جَشَع
1445	prejudice	تَحَيَّز، جَحَف، تَحَيُّز، إِجْحاف
1446	prejudiced	تَحَيَّز، جَحَف، مُتَحَيِّز، مُجْحِف، إِجْحاف
1447	prejudicial	مُتَحَيِّز
1448	prejudicing	تَحَيَّز، جَحَف، مُتَحَيِّز، مُجْحِف، إِجْحاف، تَحَيُّز
1449	premature	سابِق أوان، غَيْر ناضِج
1450	prematurely	صُورَة مُتَعَجِّل، شَكْل مُتَعَجِّل
1451	pressing	مُلِحّ
1452	pretrial	قِبَل مُحاكَمَة، ما قِبَل تَقاضِي
1453	preventing	اِحْتَرَز، تَجَنَّب
1454	prevention	تَحَوُّط
1455	prevents	مَنَع

No.	English Word	Arabic Translation
1456	problem	إشْكال، عَقَبَة، مُشْكِلَة
1457	problematic	إشْكال
1458	problematical	إشْكال
1459	prolong	أطال
1460	prolongation	إطالَة
1461	prolonged	أطال، مُطَوَّل
1462	prolonging	أطال، إطالَة
1463	prolongs	أطال
1464	prone	مَعْرِض
1465	prosecute	قاضَى
1466	prosecuted	قاضَى
1467	prosecutes	قاضَى
1468	prosecuting	قاضَى
1469	prosecution	مُحاكَمَة، مُقاضاة
1470	protest	اِحْتاج، اِحْتِجاج
1471	protested	اِحْتاج
1472	protester	مُحْتَجّ
1473	protesting	اِحْتاج، مُحْتَجّ، اِحْتِجاج
1474	protestor	اِحْتاج، مُحْتَجّ
1475	protestors	مُحْتَجّ
1476	protracted	أطال، مُطَوَّل
1477	protraction	إطالَة
1478	provoke	اِسْتَفَزّ، حَرَّض، تَحْرِيض، اِسْتِفْزاز
1479	provoked	اِسْتَفَزّ، حَرَّض
1480	provokes	اِسْتَفَزّ، حَرَّض
1481	provoking	اِسْتَفَزّ، حَرَّض، تَحْرِيض، اِسْتِفْزاز
1482	punished	عاقَب، مُعاقِب
1483	punishes	عاقَب
1484	punishing	عاقَب، مُعاقِب
1485	punishment	عِقاب
1486	punitive	تَأْدِيب
1487	purport	زَعَم، وَهِم
1488	purported	زَعَم، وَهِم
1489	purportedly	شَكْل مَزْعُوم
1490	purporting	زَعَم، وَهِم
1491	question	اِسْتَجْوَب، سَأل، تَساؤُل، تَساءَل، شَكَّك
1492	questionable	مَشْكُوك فِي، مَحَلّ تَساؤُل، مَحَلّ شَكّ، مَوْضِع شَكّ، مَوْضِع تَساؤُل
1493	questionably	شَكْل مَشْكُوك بِ
1494	questioned	اِسْتَجْوَب، سَأل، تَساؤُل، تَساءَل، شَكَّك
1495	questioning	اِسْتَجْوَب، سَأل، تَساؤُل، تَساءَل، شَكَّك
1496	quit	اِسْتَقال، تَرَك
1497	quitting	اِسْتَقال، تَرَك، اِسْتِقالَة
1498	racketeer	اِحْتال، مُحْتال
1499	racketeering	اِحْتال، مُحْتال، اِحْتِيال، اِحْتِيال مالِيّ
1500	rationalization	تَرْشِيد
1501	rationalize	أرْشَد
1502	rationalized	أرْشَد
1503	rationalizes	أرْشَد
1504	rationalizing	أرْشَد، تَرْشِيد
1505	reassessment	إعادَة تَقْيِيم، إعادَة تَقْدِير
1506	reassign	أعاد تَخْصِيص، أعاد تَعْيِين، أعاد تَكْلِيف
1507	reassigned	أعاد تَخْصِيص، أعاد تَعْيِين، أعاد تَكْلِيف

No.	English Word	Arabic Translation
1508	reassigning	أعاد تَخْصِيص، أعاد تَعْيِين، أعاد تَكْلِيف، إعادَة تَعْيِين، أعاد تَكْلِيف، إعادَة تَخْصِيص
1509	reassignment	إعادَة تَعْيِين، أعاد تَكْلِيف، إعادَة تَخْصِيص
1510	reassigns	أعاد تَخْصِيص، أعاد تَعْيِين، أعاد تَكْلِيف، أعاد تَوْزِيع
1511	recall	اِسْتَدْعَى، اِسْتِدْعاء
1512	recalled	اِسْتَدْعَى، مُسْتَدْعَى
1513	recalling	اِسْتَدْعَى، اِسْتِدْعاء
1514	recession	اِنْكِماش، رُكُود، كَساد
1515	recessionary	رُكُود، اِنْكِماش
1516	reckless	طائِش، تَهَوُّر، إهْمال
1517	recklessly	بِلا مُبالاة
1518	recklessness	تَهَوُّر، إهْمال
1519	redact	شَطَب
1520	redacted	شَطَب، مَشْطُوبٌ
1521	redacting	شَطَب، مَشْطُوبٌ
1522	redaction	شَطْب
1523	redefault	أعاد سَداد، إعادَة سَداد
1524	redefaulted	أعاد سَداد
1525	redefaults	أعاد سَداد
1526	redress	نَصَّف، صَحّ، تَدارَك
1527	redressed	نَصَّف، صَحّ، تَدارَك، مُصَحِّح
1528	redressing	نَصَّف، صَحّ، تَدارَك، تَصْحِيح
1529	refusal	أنْكَر، رَفَض، اِمْتَنَع، اِمْتِناع
1530	refuse	أنْكَر، رَفَض، اِمْتَنَع
1531	refused	أنْكَر، رَفَض، اِمْتَنَع، مَرْفُوض
1532	refusing	أنْكَر، رَفَض، اِمْتَنَع، اِمْتِناع
1533	reject	رَفَض
1534	rejected	رَفَض
1535	rejecting	رَفَض، مَرْفُوض
1536	rejection	رَفْض
1537	relinquish	تَنازَل، تَخَلّى
1538	relinquished	تَنازَل، تَخَلّى
1539	relinquishes	تَنازَل، تَخَلّى
1540	relinquishing	تَنازَل، تَخَلّى
1541	relinquishment	تَنازُل
1542	reluctance	عَزُوف، إحْجام
1543	reluctant	مِحْجَم
1544	renegotiate	أعاد تَفاوُض
1545	renegotiated	أعاد تَفاوُض
1546	renegotiates	أعاد تَفاوُض
1547	renegotiating	أعاد تَفاوُض، إعادَة تَفاوُض
1548	renegotiation	مُفاوَضَة جَدِيد، إعادَة تَفاوُض
1549	renounce	تَنازَل، تَخَلّى
1550	renounced	تَنازَل، تَخَلّى
1551	renouncement	تَخَلِّي، تَنازُل
1552	renounces	تَنازَل، تَخَلّى
1553	renouncing	تَنازَل، تَخَلّى
1554	reparation	تَعْوِيض
1555	repossessed	اِسْتَرَدّ مِلْكِيَّة
1556	repossesses	اِسْتَرَدّ مِلْكِيَّة
1557	repossessing	اِسْتَرَدّ مِلْكِيَّة
1558	repossession	اِسْتِرْداد مِلْكِيَّة، اِسْتِرْجاع مِلْكِيَّة، اِسْتِعادَة مِلْكِيَّة
1559	repudiate	تَنَصَّل

No.	English Word	Arabic Translation
1560	repudiated	تَنَصَّل
1561	repudiates	تَنَصَّل
1562	repudiating	تَنَصَّل
1563	repudiation	التَّنَصُّلُ
1564	resign	تَنَحَّى، اِسْتَقال
1565	resignation	اِسْتِقالَة
1566	resigned	تَنَحَّى، اِسْتَقال
1567	resigning	تَنَحَّى، اِسْتَقال، اِسْتِقالَة
1568	resigns	تَنَحَّى، اِسْتَقال
1569	restate	أعاد تَأكِيد، كَرَّر
1570	restated	أعاد تَأكِيد، كَرَّر
1571	reassessment	إعادَة تَقْيِيم، إعادَة تَقْدِير
1572	restates	أعاد تَأكِيد، كَرَّر
1573	restating	أعاد تَأكِيد، كَرَّر، أعاد تَأكِيد
1574	restructure	أعاد هَيْكَلَة، أعاد تَنْظِيم، إعادَة تَنْظِيم، إعادَة هَيْكَلَة
1575	restructured	أعاد هَيْكَلَة، أعاد تَنْظِيم
1576	restructures	أعاد هَيْكَلَة، أعاد تَنْظِيم
1577	restructuring	أعاد هَيْكَلَة، أعاد تَنْظِيم، إعادَة تَنْظِيم، إعادَة هَيْكَلَة
1578	restructurings	أعاد هَيْكَلَة، أعاد تَنْظِيم، إعادَة تَنْظِيم، إعادَة هَيْكَلَة
1579	retaliate	اِنْتَقَم
1580	retaliated	اِنْتَقَم، مُنْتَقِم
1581	retaliates	اِنْتَقَم
1582	retaliating	اِنْتَقَم، مُنْتَقِم
1583	retaliation	اِنْتِقام
1584	retaliatory	اِنْتِقام
1585	retribution	قِصاص
1586	revocation	نَقْض
1587	revoke	نَقَض
1588	revoked	نَقَض
1589	revoking	نَقَض، مَنْقُوض، نَقْض
1590	ridicule	اِسْتَهْزَأ، سَخَّر
1591	ridiculed	اِسْتَهْزَأ، سَخَّر
1592	ridiculing	اِسْتَهْزَأ، سَخَّر، سُخْرِيَّة
1593	riskier	أكْثَر مُخاطَرَة، أعْلَى مُخاطَرَة، أكْثَر خُطُورَة، أعْلَى خُطُورَة
1594	riskiest	أكْثَر مُخاطَرَة، أعْلَى مُخاطَرَة، أكْثَر خُطُورَة، أعْلَى خُطُورَة، أخْطَر
1595	risky	خَطِير، خَطَر
1596	sabotage	خَرَّب، أفْسَد
1597	sacrifice	أضْحَى
1598	sacrificed	أضْحَى
1599	sacrificial	فدائِي
1600	sacrificing	أضْحَى
1601	scandals	فَضِيحَة
1602	scandalous	مَخْزِيّ
1603	scrutinize	تَمْحِيص
1604	scrutinized	دَقَّق
1605	scrutinizes	دَقَّق
1606	scrutinizing	دَقَّق، تَمْحِيص
1607	scrutiny	تَمْحِيص
1608	seize	اِحْتَجَز، صادَر
1609	seized	اِحْتَجَز، صادَر، مُحْتَجَز، مُصادَرَة
1610	seizes	اِحْتَجَز، صادَر
1611	seizing	اِحْتَجَز، صادَر، مُحْتَجَز، مُصادَرَة

No.	English Word	Arabic Translation
1612	sentenced	مَحْكُوم عَلَى
1613	sentencing	صَدَر حُكْم، صُدُور حُكْم
1614	serious	جادّ، خَطِير
1615	seriously	شَكْل جِدِّيّ، شَكْل خَطِير، نَحْو خَطِير
1616	seriousness	خُطُورَة
1617	setback	نَكْسَة، اِنْتِكاس
1618	sever	بَتَر
1619	severe	حادّ، قاسِي، خَطِير
1620	severed	مَقْطُوع
1621	severely	شَكْل حادّ
1622	severity	حِدَّة
1623	sharply	شَكْل حادّ
1624	shocked	مَذْهُول
1625	shortage	شَحّ، عَجْز
1626	shortfall	عَجْز
1627	shrinkage	اِنْحِسار، تَقَلُّص، تَضاؤُل
1628	shut	أَغْلَق، مُغْلَق
1629	shutdown	إِغْلاق
1630	shuts	أَغْلَق
1631	shutting	أَغْلَق، إِيقاف
1632	slander	اِفْتَرَى، اِفْتِراء
1633	slandered	اِفْتَرَى
1634	slanderous	اِفْتِراء
1635	slippage	اِنْزِلاق
1636	slow	بَطُأ، بَطِيء
1637	slowdown	تَراجُع
1638	slowed	بَطُأ، بَطِيء
1639	slower	بَطُأ
1640	slowest	الأَكْثَرَ بُطْء، الأَكْثَرَ رُكُود
1641	slowing	بَطُأ
1642	slowly	شَكْل بَطِيء، نَحْو بَطِيء، صُورَة بَطِيء، وَتِيرَة بَطِيء
1643	slowness	بُطْء
1644	sluggish	راكِد، كَسُول، بَطِيء
1645	sluggishly	شَكْل بَطِيء، نَحْو بَطِيء
1646	sluggishness	تَثاقُل، بُطْء، خُمُول
1647	solvency	اِسْتِقْرار مالِيّ، كَفاءَة مالِيّ، مِلائَة مالِيّ
1648	spam	بَرِيد مُزْعِج، بَرِيد عَشْوائِيّ
1649	spammers	بَرِيد مُزْعِج، بَرِيد عَشْوائِيّ
1650	spamming	بَرِيد مُزْعِج، بَرِيد عَشْوائِيّ
1651	staggering	صادِم
1652	stagnant	راكِد
1653	stagnate	رَكَد، رُكُود
1654	stagnated	رَكَد، راكِد
1655	stagnates	رَكَد
1656	stagnating	رَكَد، راكِد
1657	stagnation	رُكُود
1658	standstill	مُتَوَقِّف
1659	stolen	مَسْرُوق
1660	stops	وَقَّف، تَوَقَّف
1661	stoppage	عَطَّل
1662	stopped	وَقَّف، مُتَوَقِّف
1663	stopping	وَقَّف، تَوَقَّف

No.	English Word	Arabic Translation
1664	strain	جَهَد، إِجْهاد
1665	strained	جَهَد، مُجْهَد
1666	straining	جَهَد، إِجْهاد
1667	stress	ضَغَط، ضَغْط
1668	stressed	مُتَوَتِّر
1669	stressful	مُقْلِق، مُجْهَد
1670	stressing	جَهَد، إِجْهاد
1671	stringent	صارِم، مُشَدِّد
1672	subjected	خَضَع، خاضِع
1673	subjecting	خَضَع، خاضِع
1674	subjection	خُضُوع
1675	subpoena	اِسْتَدْعَى مَحْكَمَة، أَمْر قَضائِيّ، مُذَكِّرَة اِسْتِدْعاء، اِسْتِدْعاء قَضائِيّ، دَعْوَة مَحْكَمَة
1676	subpoenaed	اِسْتَدْعَى مَحْكَمَة
1677	substandard	دُون مُسْتَوَى، رَدِيء
1678	sue	قاضَى
1679	suffer	عانَى
1680	suffered	عانَى
1681	suffering	عانَى، مُعاناة
1682	suffers	عانَى
1683	suing	قاضَى، مُقاضاة
1684	summoned	أَمْر قَضائِيّ، مُذَكِّرَة اِسْتِدْعاء، اِسْتِدْعاء قَضائِيّ، دَعْوَة مَحْكَمَة، تَمّ اِسْتِدْعاء
1685	summoning	أَمْر قَضائِيّ، مُذَكِّرَة اِسْتِدْعاء، اِسْتِدْعاء قَضائِيّ، دَعْوَة مَحْكَمَة
1686	summons	جَرَى اِسْتِدْعاء
1687	susceptibility	قابِلِيَّة
1688	susceptible	سَرِيع تَأَثُّر
1689	suspect	اِشْتَبَه
1690	suspected	اِشْتَبَه، مُشْتَبَه بِ
1691	suspend	وَقَّف، عَلَّق
1692	suspended	وَقَّف، عَلَّق
1693	suspending	وَقَّف، عَلَّق، مَوْقُوف، مُعَلَّق
1694	suspends	وَقَّف، عَلَّق
1695	suspension	إِيقاف
1696	suspicion	اِشْتِباه
1697	suspicious	مُرِيب
1698	suspiciously	شَكْل مُرِيب، شَكْل مُثِير رِيبَة
1699	taint	لَطَّخ
1700	tainted	لَطَّخ
1701	tainting	لَطَّخ
1702	tampered	مُزَوَّر
1703	tense	تَوَتُّر، مُتَوَتِّر
1704	terminate	أَلْغَى، فَسَخ
1705	terminated	أَلْغَى، فَسَخ، مُلْغَى
1706	terminates	أَلْغَى، فَسَخ
1707	terminating	أَلْغَى، فَسَخ
1708	termination	إِنْهاء
1709	testify	اِعْتَرَف
1710	testifying	اِعْتَرَف
1711	threat	هَدَّد
1712	threaten	هَدَّد
1713	threatened	هَدَّد
1714	threatening	هَدَّد، تَهْدِيد
1715	threatens	هَدَّد

No.	English Word	Arabic Translation
1716	tightening	تَشْدِيد
1717	tolerate	تَهاوَن، تَساهَل، تَحَمَّل
1718	tolerated	تَهاوَن، تَساهَل، تَحَمَّل
1719	tolerates	تَهاوَن، تَساهَل، تَحَمَّل
1720	tolerating	تَهاوَن، تَساهَل، تَحَمَّل، مُتَهاوِن، مُتَساهِل
1721	toleration	تَحَمُّل
1722	tortuous	شاقّ، مَقْعَد
1723	tortuously	شَكْل مُعَقَّد، نَحْو مُعَقَّد
1724	tragedy	مَأْساة، مُصِيبَة
1725	tragic	مَأْسَوِيّ
1726	tragically	شَكْل مَأْسَوِيّ
1727	traumatic	مُؤْلِم
1728	trouble	مُشْكِلَة، مَتاعِب، مُشْكِلَة
1729	troubled	مُضْطَرِب
1730	turbulence	تَقَلُّب، اِضْطِراب
1731	turmoil	اِضْطِراب
1732	unable	عاجِز، غَيْر قادِر، لا اِسْتَطاع
1733	unacceptable	مَرْفُوض، مُسْتَهْجَنٌ
1734	unacceptably	شَكْل مَرْفُوض
1735	unaccounted	غَيْر مَحْسُوب
1736	unannounced	مُفاجِئ، غَيْر مُعْلَن
1737	unanticipated	غَيْر مُتَوَقَّع
1738	unapproved	غَيْر مُصَرَّح بِ، غَيْر مُعْتَمَد، غَيْر مُوافِق عَلَى
1739	unattractive	غَيْر مُلْفِت، غَيْر جَذّاب
1740	unauthorized	غَيْر مُرَخَّص، غَيْر مُصَرَّح بِ، غَيْر مُصَرَّح
1741	unavailability	عَدَم تَوَفُّر
1742	unavailable	غَيْر مَوْجُود، غَيْر مُتاح
1743	unavoidable	لا أَمْكَن تَجَنُّب، حَتْمِيّ
1744	unavoidably	لا أَمْكَن تَجَنُّب
1745	unaware	جَهِل
1746	uncollectable	غَيْر قابِل تَحْصِيل، غَيْر مُحَصَّل
1747	uncollected	لَم تَمّ تَحْصِيل، غَيْر مُحَصَّل
1748	uncollectibility	صُعُوبَة تَحْصِيل
1749	uncollectible	غَيْر قابِل تَحْصِيل، لا أَمْكَن تَحْصِيل، مُسْتَحِيل تَحْصِيل
1750	uncollectibles	غَيْر قابِل تَحْصِيل، لا أَمْكَن تَحْصِيل، مُسْتَحِيل تَحْصِيل
1751	uncompetitive	غَيْر تَنافُس
1752	uncompleted	غَيْر مُكْتَمَل
1753	unconscionable	مُفْرِط، جائِر، غَيْر مَعْقُول
1754	unconscionably	شَكْل جائِر، نَحْو جائِر
1755	uncontrollable	خارِج سَيْطَرَة
1756	uncontrolled	غَيْر مُنْضَبِط
1757	uncorrected	غَيْر مُعَدَّل، غَيْر مُصَحَّح
1758	uncover	اِكْتَشَف
1759	uncovered	اِكْتَشَف
1760	uncovering	اِكْتَشَف
1761	uncovers	اِكْتَشَف
1762	undeliverable	مُسْتَحِيل تَسْلِيم، غَيْر قابِل تَسْلِيم، لا أَمْكَن تَسْلِيم
1763	undelivered	لَم تَمّ تَسْلِيم، لَم تَمّ تَسْلِيم، غَيْر قابِل تَسْلِيم
1764	undercut	خَفَّض
1765	undercutting	خَفَّض
1766	underestimate	قَلَّل مِن تَقْدِير
1767	underestimated	قَلَّل مِن تَقْدِير

No.	English Word	Arabic Translation
1768	underestimating	قَلَّل مِن تَقْدِير
1769	underfunded	غَيْر مُمَوَّل، ضَعِيف تَمْوِيل
1770	undermine	قَوَّض
1771	undermined	قَوَّض
1772	undermines	قَوَّض
1773	undermining	قَوَّض
1774	underpaid	أَجْرَ زَهِيد
1775	underpayment	سَداد مُنْخَفِض، دَفْع مُنْخَفِض
1776	underperform	أداء دُون مُسْتَوَى، غَيْر مُحَقِّق طَمُوح
1777	underperformance	أداء ضَعِيف، ضُعْف أداء
1778	underperformed	أَدَّى دُون مُسْتَوَى، ضَعِيف أداء
1779	underperforming	غَيْر مُحَقِّق هَدَف، أداء دُون تَوَقُّع، أداء ضَعِيف
1780	underperforms	أَدَّى دُون مُسْتَوَى
1781	underproduced	ناقِص إِنْتاج
1782	underproduction	عَجْز فِي إِنْتاج، إِنْتاج غَيْر كافِي، نَقْص إِنْتاج، قَصْر إِنْتاج
1783	underreporting	عَدَم إِبْلاغ كامِل، قَصْر فِي تَقْرِير
1784	understate	قَلَّل مِن شَأْن
1785	understated	قَلَّل مِن شَأْن
1786	understatement	بَخَس
1787	understates	قَلَّل مِن شَأْن
1788	understating	قَلَّل مِن شَأْن، تَخْفِيف مِن أَهَمِّيَّة
1789	underutilization	قَصْر فِي اِسْتِخْدام
1790	underutilized	غَيْر مُسْتَغَلّ كامِل، غَيْر قَلِيل اِسْتِخْدام
1791	undesirable	غَيْر مَرْغُوب، غَيْر مُسْتَحَبّ
1792	undesired	غَيْر مَرْضِيّ، غَيْر مُفَضَّل
1793	undetected	غَيْر مُكْتَشِف، لَم تَمّ كَشْف، غَيْر مَرْصُود
1794	undetermined	مُبْهَم، غَيْر مُحَدَّد، غَيْر مَعْلُوم
1795	undisclosed	غَيْر مُعْلَن، غَيْر مَكْشُوف، غَيْر مُفْصِح عَن، لَم كَشَف عَن، غَيْر مَعْرُوف
1796	undocumented	غَيْر مَوْثِق
1797	undue	لا داعِي لِ، غَيْر مُبَرِّر، غَيْر لازِم
1798	unduly	شَكْل مُفْرِط، نَحْو مُفْرِط
1799	uneconomic	مُكَلِّف، لَيس مَجْدِي اِقْتِصادِيّ، غَيْر مَجْدِي اِقْتِصادِيّ
1800	uneconomical	مُكَلِّف، لَيس مَجْدِي اِقْتِصادِيّ، غَيْر مَجْدِي اِقْتِصادِيّ
1801	uneconomically	شَكْل غَيْر اِقْتِصادِيّ
1802	unemployed	عاطِل
1803	unemployment	بِطالَة
1804	unethical	غَيْر أَخْلاقِيّ، مُنافِي خُلُق، مُناقِض خُلُق، مُخالِف خُلُق
1805	unethically	شَكْل غَيْر أَخْلاقِيّ، نَحْو غَيْر أَخْلاقِيّ، طَرِيقَة غَيْر أَخْلاقِيّ
1806	unexcused	غَيْر مُبَرِّر، دُون عُذْر
1807	unexpected	غَيْر مُتَوَقَّع، مُفاجِئ، طارِئ
1808	unexpectedly	نَحْو غَيْر مُتَوَقَّع، شَكْل غَيْر مُتَوَقَّع، صُورَة غَيْر مُتَوَقَّع، شَكْل مُفاجِئ، نَحْو مُفاجِئ
1809	unfair	جائِر، مُجْحِف، غَيْر عادِل، لَيس عادِل
1810	unfairly	شَكْل غَيْر عادِل، نَحْو غَيْر عادِل، طَرِيقَة غَيْر عادِل
1811	unfavorability	عَدَم تَفْضِيل
1812	unfavorable	غَيْر مُفَضَّل، سَلْبِيّ
1813	unfavorably	شَكْل غَيْر مُفَضَّل، صُورَة غَيْر مُفَضَّل
1814	unfavourable	غَيْر مُفَضَّل
1815	unfeasible	غَيْر مَلام
1816	unfit	غَيْر لائِق
1817	unfitness	عَدَم مُلاءَمَة، عَدَم أَهْلِيَّة
1818	unforeseeable	غَيْر قابِل تَنَبُّؤ، لا أَمْكَن تَنَبُّؤ
1819	unforeseen	مُفاجِئ، غَيْر مُخَطَّط لِ

No.	English Word	Arabic Translation
1820	unforseen	مُفاجِئ، غَيْر مُخَطَّط لِ
1821	unfortunate	مُؤْسِف
1822	unfortunately	سُوء حَظّ، مَع أَسَف، أَسَف
1823	unfounded	دُون دَلِيل، بِلا أَساس
1824	unfriendly	غَيْر وُدِّيّ
1825	unfulfilled	غَيْر مُكْتَمَل، غَيْر مُنْجَز
1826	unfunded	غَيْر مَدْعُوم مالِيّ، غَيْر مُغَطّى
1827	uninsured	دُون تَغْطِيَة تَأْمِين، بِلا تَأْمِين، غَيْر مُغَطّى تَأْمِين، غَيْر مُؤْمِن، دُون تَأْمِين
1828	unintended	غَيْر مَقْصُود، غَيْر مُتَعَمَّد
1829	unintentional	غَيْر مَقْصُود، غَيْر مُتَعَمَّد، غَيْر مُخَطَّط لِ، دُون قَصَد
1830	unintentionally	شَكْل غَيْر مُتَعَمَّد، عَن غَيْر قَصَد، شَكْل غَيْر مَقْصُود
1831	unjust	ظالِم
1832	unjustifiable	غَيْر مُبَرِّر، غَيْر مُبَرِّر، غَيْر قابِل تَبْرِير
1833	unjustifiably	دُون سَبَب، شَكْل غَيْر مُبَرِّر، طَرِيقَة غَيْر مَقْبُول
1834	unjustified	غَيْر مُبَرِّر، دُون مُبَرِّر، بِلا مُبَرِّر
1835	unjustly	شَكْل غَيْر عادِل، دُون وَجْه حَقّ، شَكْل مُجْحِف، شَكْل غَيْر مُنْصِف
1836	unknowing	دُون إِدْراك، دُون عِلْم، دُون مَعْرِفَة
1837	unknowingly	دُون مَعْرِفَة، دُون دِرايَة، دُون إِدْراك
1838	unlawful	غَيْر قانُونِيّ، مُخالِف قانُون، مَنْفَى قانُون
1839	unlawfully	شَكْل غَيْر قانُونِيّ، طَرِيقَة غَيْر قانُونِيّ، شَكْل مُخالِف قانُون
1840	unlicensed	غَيْر مُرَخَّص، دُون تَرْخِيص، دُون رُخْصَة
1841	unliquidated	غَيْر مُصَفّى
1842	unmarketable	غَيْر رائِج
1843	unmerchantable	غَيْر جَيِّد تِجارَة، غَيْر قابِل تِجارَة، غَيْر قابِل تَسْوِيق، غَيْر صالِح بَيْع
1844	unmeritorious	غَيْر جَدِير تَقْدِير
1845	unnecessarily	لا داعِي لِ، شَكْل غَيْر ضَرُورِيّ، بِلا داعِي
1846	unnecessary	لا داعِي لِ، غَيْر ضَرُورِيّ
1847	unneeded	غَيْر لازِم
1848	unobtainable	غَيْر قابِل حُصُول، بَعِيد مَنال
1849	unoccupied	شاغِر، غَيْر مَأْهُول
1850	unpaid	غَيْر مَدْفُوع
1851	unperformed	غَيْر مُنْجَز
1852	unplanned	غَيْر مُتَوَقَّع، دُون تَخْطِيط
1853	unpopular	غَيْر رائِج
1854	unpredictability	لا أَمْكَن تَنَبُّؤ
1855	unpredictable	مُتَقَلِّب، لا أَمْكَن تَنَبُّؤ، غَيْر قابِل تَنَبُّؤ
1856	unpredictably	شَكْل مُتَقَلِّب، صُورَة مُتَقَلِّب
1857	unpredicted	غَيْر مُتَوَقَّع، غَيْر مُتَنَبِّئ بِ
1858	unproductive	غَيْر مُنْتِج، غَيْر مُثْمِر
1859	unprofitability	اِنْعِدام جَداء مالِيّ
1860	unprofitable	غَيْر مُرْبِح، غَيْر مَجْدِي مالِيّ
1861	unqualified	غَيْر كُفُوء، غَيْر مُؤَهَّل
1862	unrealistic	غَيْر واقِعِيّ
1863	unreasonable	غَيْر مَعْقُول، غَيْر مَنْطِقِيّ
1864	unreasonableness	عَدَم مَعْقُولِيَّة
1865	unreasonably	شَكْل غَيْر مَعْقُول، شَكْل غَيْر مُنْصِف، شَكْل غَيْر مَنْطِقِيّ
1866	unreceptive	غَيْر مُسْتَجِيب
1867	unrecoverable	لا أَمْكَن اِسْتِعادَة، غَيْر قابِل اِسْتِرْداد، لا أَمْكَن اِسْتِرْداد
1868	unrecovered	غَيْر قابِل اِسْتِرْداد
1869	unreimbursed	دُون تَعْوِيض، بِلا تَعْوِيض
1870	unreliable	غَيْر مَوْثُوق
1871	unremedied	غَيْر مُعالِج، غَيْر مُصَحِّح

No.	English Word	Arabic Translation
1872	unreported	غَيْر مَبْلَغ عَن
1873	unresolved	غَيْر مَحْلُول
1874	unrest	اِضْطِراب
1875	unsafe	خَطَر، غَيْر آمِن
1876	unsalable	غَيْر قابِل بَيْع
1877	unsaleable	غَيْر قابِل بَيْع
1878	unsatisfactory	غَيْر مَرَضِيّ
1879	unsatisfied	غَيْر راضِي
1880	unsavory	مُنَفِّر
1881	unscheduled	غَيْر مَجْدُول
1882	unsellable	غَيْر قابِل بَيْع
1883	unsold	غَيْر مُباع
1884	unsound	غَيْر مَتِين
1885	unstabilized	غَيْر مُسْتَقِرّ
1886	unstable	غَيْر مُسْتَقِرّ
1887	unsubstantiated	غَيْر مُؤَكَّدٍ
1888	unsuccessful	فاشِل، غَيْر ناجِح
1889	unsuccessfully	شَكْل فاشِل، شَكْل غَيْر ناجِح، نَحْو غَيْر ناجِح
1890	unsuitability	عَدَم اِنْسِجام
1891	unsuitable	غَيْر مَلام، غَيْر مُناسِب
1892	unsuitably	شَكْل غَيْر مَلام، نَحْو غَيْر مَلام
1893	unsuited	غَيْر مُطَابِقٌ
1894	unsure	مُتَرَدِّد، غَيْر واثِق
1895	unsuspected	غَيْر مُتَوَقَّع
1896	unsuspecting	غَيْر مُدْرِك، غَيْر وَعَى
1897	unsustainable	غَيْر مُسْتَدام
1898	untenable	غَيْر مَنْطِقِيّ
1899	untimely	فِي غَيْر وَقْت، قِبَل أوان
1900	untrusted	غَيْر مَأْمُون
1901	untruth	كِذْب
1902	untruthful	غَيْر أَمِين
1903	untruthfully	شَكْل غَيْر مَوْثُوق، شَكْل غَيْر صادِق، شَكْل كاذِب
1904	untruthfulness	كِذْب
1905	unusable	غَيْر صالِح اِسْتِعْمال، غَيْر صالِح اِسْتِخْدام، غَيْر قابِل اِسْتِخْدام
1906	unwanted	غَيْر مَرْغُوب، غَيْر مَرْحَب بِ
1907	unwarranted	غَيْر مُبَرِّر
1908	unwelcome	غَيْر مَرْحَب بِ
1909	unwilling	عَدَم رَغْبَة
1910	unwillingness	عَزُوف
1911	upset	مُسْتاء
1912	urgency	إِلْحاح
1913	urgent	مُلِحّ
1914	usurious	مُرابِي
1915	usurp	اِنْتَزَع، اِغْتَصَب
1916	usurped	اِنْتَزَع، اِغْتَصَب، مُنْتَزَع
1917	usurping	اِنْتَزَع، اِغْتَصَب، اِنْتِزاع، اِسْتِيلاء
1918	usurps	اِنْتَزَع، اِغْتَصَب
1919	usury	اِنْتِهازِيّ مالِيّ، اِسْتِغْلال مالِيّ
1920	vandalism	عَبَث، تَخْرِيب
1921	verdict	صُدُور حُكْم
1922	vetoed	نَقْض، مَنْقُوض
1923	victims	ضَحِيَّة

No.	English Word	Arabic Translation
1924	violate	اِنْتَهَك
1925	violated	اِنْتَهَك، مُنْتَهَك
1926	violates	اِنْتَهَك
1927	violating	اِنْتَهَك، مُنْتَهَك
1928	violation	اِنْتِهاك
1929	violative	مُنْتَهَك
1930	violator	مُنْتَهَك
1931	violence	شِدَّة، عُنْف
1932	violent	عَنِيف
1933	violently	شَكْل عَنِيف، نَحْو عَنِيف
1934	vitiate	أَفْسَد
1935	vitiated	أَفْسَد، مُفْسِد
1936	vitiates	أَفْسَد
1937	vitiating	أَفْسَد
1938	vitiation	إِفْساد
1939	voided	باطِل
1940	voiding	بَطَل
1941	volatile	مُتَقَلِّب، غَيْر مُسْتَقِرّ
1942	volatility	تَقَلُّب، تَذَبْذُب
1943	vulnerability	عالِي تَأَثُّر
1944	vulnerable	هَشّ
1945	vulnerably	شَكْل هَشّ
1946	warn	حَذَّر، أَنْذَر
1947	warned	حَذَّر، أَنْذَر
1948	warning	حَذَّر، أَنْذَر
1949	warns	حَذَّر، أَنْذَر
1950	wasted	ضائِع، مُهْدَر
1951	wasteful	ضائِع
1952	wasting	ضائِع
1953	weak	أَضْعَف، ضَعِيف، هَزِيل
1954	weaken	أَضْعَف
1955	weakened	أَضْعَف، ضَعِيف، هَزِيل
1956	weakening	أَضْعَف، ضَعِيف، هَزِيل
1957	weakens	أَضْعَف
1958	weaker	أَضْعَف
1959	weakest	أَكْثَر ضُعْف
1960	weakly	شَكْل ضَعِيف، نَحْو ضَعِيف
1961	weakness	ضُعْف
1962	willfully	شَكْل مُتَعَمَّد
1963	worry	قَلَق، خَوْف
1964	worrying	قَلَق
1965	worse	أَسْوَأ
1966	worsen	تَفاقَم
1967	worsened	تَفاقَم
1968	worsening	تَفاقَم، مُتَدَهْوِر
1969	worsens	تَفاقَم
1970	worst	أَكْثَر سُوء
1971	worthless	لا قِيمَة لِ، بِلا قِيمَة
1972	writedown	أَهْلَك، أَهْلاك
1973	writedowns	أَهْلَك
1974	writeoff	شَطْب دِين
1975	writeoffs	شَطْب دِين

No.	English Word	Arabic Translation
1976	wrong	مُخْطِئ، خاطِئ، نَحْو خاطِئ، شَكْل خاطِئ
1977	wrongdoing	مُخالِف، مُخْطِئ، خاطِئ
1978	wrongful	مُخْطِئ، خاطِئ، جائِر
1979	wrongfully	شَكْل خاطِئ، نَحْو خاطِئ، شَكْل غَيْر عادِل، نَحْو غَيْر عادِل
1980	wrongly	شَكْل خاطِئ، نَحْو خاطِئ

Table A2. (b-3.i) Negative Arabic One Word Dimensional (*N=1,105*)

No.	One Word Dimensional
1	آذَى
2	آل
3	أثار
4	أثْقال
5	أثْقَل
6	أجَّل
7	أجْبَر
8	أحال
9	أحْرَج
10	أحْرَق
11	أخْطَأ
12	أخْطَر
13	أخْفَى
14	أخْمَد
15	أدان
16	أذَى
17	أذْعَن
18	أرْبَك
19	أرْجَأ
20	أرْشَد
21	أرْغَم
22	أرْهَق
23	أزال
24	أزَّم
25	أزْعَج
26	أزْمَة
27	أساء
28	أسَف
29	أسْقَط
30	أسْوَأ
31	أشَدّ
32	أصاب
33	أضْحَى
34	أضْعَف
35	أطال
36	أعاق
37	أعْفَى
38	أغْضَب
39	أغْفَل
40	أغْلَق
41	أفْسَد
42	أفْشَى
43	أفْصَح
44	أفْقَد
45	أفْلَس
46	أقْسَى
47	أقْفَل
48	أقْلَق
49	ألَحّ
50	ألْزَم

No.	One Word Dimensional
51	أَلْغَى
52	أَمَر
53	أَنْذَر
54	أَنْكَر
55	أَنْهَى
56	أَهان
57	أَهْلاك
58	أَهْلَك
59	أَهْمَل
60	أَوْرَط
61	وَخِّر
62	إِبْراء
63	إِبْطال
64	إِبْعاد
65	إِتْلاف
66	إِثارَة
67	إِثْم
68	إِجْبار
69	إِجْحاف
70	إِجْرامِيّ
71	إِجْلاء
72	إِجْهاد
73	إِحْباط
74	إِحْجاف
75	إِحْجام
76	إِحْراق
77	إِحْلال
78	إِخْفاء
79	إِخْفاق
80	إِخْلاء
81	إِخْلال
82	إِدانَة
83	إِذْعان
84	إِرْباك
85	إِرْغام
86	إِزاحَة
87	إِزالَة
88	إِزْعاج
89	إِساءَة
90	إِسْعاف
91	إِشْكال
92	إِشْكالِيّ
93	إِصابَة
94	إِطالَة
95	إِعاقَة
96	إِعْتام
97	إِعْراض
98	إِعْسار
99	إِغْفال
100	إِغْلاق
101	إِفْراج
102	إِفْساد

No.	One Word Dimensional
103	إِفْشاء
104	إِفْلاس
105	إِقالَة
106	إِقْفال
107	إِكْراه
108	إِلْحاح
109	إِلْزام
110	إِلْزامِيّ
111	إِلْغاء
112	إِنْذار
113	إِنْقاذ
114	إِنْكار
115	إِنْهاء
116	إِهانَة
117	إِهْمال
118	إِيقاف
119	التَّنَصُّلُ
120	بائِد
121	باطِل
122	بالَغ
123	بالِغ
124	باهِت
125	باهِظ
126	بطلان
127	بَتَر
128	بَخَس
129	بَذاء
130	بَذِيء
131	بَراءَة
132	بَرَّأ
133	بَرَّر
134	بَشِع
135	بَطَل
136	بَطِيء
137	بَطَّأ
138	بَعُد
139	بَغِيض
140	بَلاء
141	بُطْء
142	بِطالَة
143	تافِه
144	تَآكَل
145	تَآكُل
146	تَآمَر
147	تَآمُر
148	تَأَخَّر
149	تَأَخُّر
150	تَأَلَّف
151	تَأْجِيل
152	تَأْخِير
153	تَأْدِيب
154	تَأْزِيم

No.	One Word Dimensional
155	تَباطُؤ
156	تَبايُن
157	تَبَرَّأ
158	تَبْرِئَة
159	تَثاقُل
160	تَجادَل
161	تَجاهَل
162	تَجاهُل
163	تَجَرَّد
164	تَجَنَّب
165	تَجْرِيد
166	تَجْرِيم
167	تَجْمِيد
168	تَحاشَى
169	تَحايُل
170	تَحَدَّى
171	تَحَدِّي
172	تَحَرَّش
173	تَحَرَّى
174	تَحَرُّش
175	تَحَرِّي
176	تَحَفَّظ
177	تَحَمَّل
178	تَحَمُّل
179	تَحَوُّط
180	تَحَيَّز
181	تَحَيُّز
182	تَحْذِير
183	تَحْرِيض
184	تَحْرِيف
185	تَحْقِير
186	تَخارُج
187	تَخاصَم
188	تَخَلَّص
189	تَخَلَّف
190	تَخَلَّى
191	تَخَلّص
192	تَخَلّف
193	تَخَلِّي
194	تَخْرِيب
195	تَخْفِيض
196	تَخْفِيف
197	تَداخُل
198	تَدارَك
199	تَداعِي
200	تَدَخَّل
201	تَدَخُّل
202	تَدَنَّى
203	تَدَنِّي
204	تَدَهْوَر
205	تَدَهْوُر
206	تَدْمِير

No.	One Word Dimensional
207	تَذَبْذَب
208	تَذَرَّع
209	تَذَمَّر
210	تَذَمُّر
211	تَراجَع
212	تَراجُع
213	تَراخِي
214	تَرَدَّد
215	تَرَدَّى
216	تَرَدُّد
217	تَرَك
218	تَرَوِّي
219	تَرْشِيد
220	تَرْك
221	تَرْهِيب
222	تَزْوِير
223	تَزْيِيف
224	تَساءَل
225	تَساؤُل
226	تَساهَل
227	تَسَرُّب
228	تَسْرِيح
229	تَسْوِيَة
230	تَشْتِيت
231	تَشْدِيد
232	تَشْهِير
233	تَشْوِيش
234	تَشْوِيه
235	تَصادَم
236	تَصادُم
237	تَصَدَّى
238	تَصْحِيح
239	تَصْعِيد
240	تَصْفِيَة
241	تَضاءَل
242	تَضاؤُل
243	تَضارَب
244	تَضارُب
245	تَضايَق
246	تَضْخِيم
247	تَضْلِيل
248	تَظَلَّم
249	تَعارَض
250	تَعارُض
251	تَعَثَّر
252	تَعَجَّل
253	تَعَدَّى
254	تَعَدِّي
255	تَعَسُّفِيّ
256	تَعَطَّل
257	تَعَطَّل
258	تَعْدِيل

No.	One Word Dimensional
259	تَعْطِيل
260	تَعْقِيد
261	تَعْوِيض
262	تَغاضَى
263	تَغافَل
264	تَغايَر
265	تَغَلَّب
266	تَغَيُّب
267	تَفادَى
268	تَفاقَم
269	تَفاوُت
270	تَفَشِّي
271	تَفَكُّك
272	تَقادُم
273	تَقاضِي
274	تَقَشُّف
275	تَقَصَّى
276	تَقَلَّب
277	تَقَلَّص
278	تَقْصِير
279	تَقْلِيص
280	تَقْلِيل
281	تَكاسَل
282	تَلاشَى
283	تَلاشِي
284	تَلاعَب
285	تَلاعُب
286	تَلَف
287	تَلِف
288	تَمَرُّد
289	تَمَلَّص
290	تَمَلَّص
291	تَمْحِيص
292	تَنازَل
293	تَنازُع
294	تَنازُل
295	تَناقَص
296	تَناقَض
297	تَناقُض
298	تَنَحَّى
299	تَنَصَّل
300	تَنْبِيه
301	تَنْدِيد
302	تَهاوَن
303	تَهاوَى
304	تَهاوُن
305	تَهَجَّم
306	تَهَجُّم
307	تَهَرَّب
308	تَهَرُّب
309	تَهَوُّر
310	تَهْدِئَة

No.	One Word Dimensional
311	تَهْدِيد
312	تَهْوِيل
313	تَوارَى
314	تَواطَأ
315	تَواطُؤ
316	تَوَتُّر
317	تَوَسَّل
318	تَوَسُّل
319	تَوَقَّف
320	تَوَقُّف
321	تَوْبِيخ
322	تُهْمَة
323	ثَبَط
324	ثَقِيل
325	ثَنَى
326	ثُغْرَة
327	جائِر
328	جابَه
329	جادَل
330	جادّ
331	جازَف
332	جانِح
333	جانِي
334	جَحَف
335	جَدَل
336	جَدّال
337	جَرَح
338	جَرِيمَة
339	جَرّ
340	جَرَّد
341	جَرَّم
342	جَسِيم
343	جَشَع
344	جَفاف
345	جَلَى
346	جَمَّد
347	جَهَد
348	جَهِل
349	جُمُود
350	جُنُوح
351	جُنْحَة
352	جِدال
353	جِنائِيّ
354	جِنايَة
355	حاجِز
356	حادِث
357	حادّ
358	حاقِد
359	حَبَس
360	حَبَط
361	حَتْمِيّ
362	حَجَب

No.	One Word Dimensional
363	حَجَز
364	حَجْب
365	حَجْز
366	حَذَف
367	حَذّر
368	حَذْف
369	حَرَج
370	حَرَم
371	حَرَّض
372	حَرَّف
373	حَصَر
374	حَظَر
375	حَظْر
376	حَمَل
377	حَمْل
378	حَنِث
379	حَيَّد
380	حُجَّة
381	حِدَّة
382	حِذْر
383	حِرْمان
384	حِقْد
385	حِيطَة
386	خائِن
387	خاب
388	خاسِر
389	خاضِع
390	خاطَر
391	خاطِئ
392	خاف
393	خامِل
394	خانَق
395	خَبَث
396	خَبِيث
397	خَدَع
398	خَذَل
399	خَراب
400	خَرَق
401	خَرَّب
402	خَرْق
403	خَزَى
404	خَسارَة
405	خَسِر
406	خَشِي
407	خَشْيَة
408	خَضَع
409	خَطَأ
410	خَطَر
411	خَطِير
412	خَفَق
413	خَفَّض
414	خَفَّف

No.	One Word Dimensional
415	خَفْض
416	خَلَط
417	خَلَل
418	خَوْف
419	خُشُونَة
420	خُصُومَة
421	خُضُوع
422	خُطُورَة
423	خُمُول
424	خِداع
425	خِذْلان
426	خِزْي
427	خِلاف
428	خِيانَة
429	دافَع
430	دَقّق
431	دَمار
432	دَمَّر
433	دَنِيء
434	دِفاعِيّ
435	ذَعِن
436	ذَنْب
437	ذُعْر
438	رادِع
439	راكِد
440	راوَغ
441	رَدَع
442	رَدِيء
443	رَدْع
444	رَشا
445	رَشْوَة
446	رَضَخ
447	رَفَض
448	رَفْض
449	رَكَد
450	رَيْب
451	رُضُوخ
452	رُكُود
453	زائِف
454	زاح
455	زَعَم
456	زَعْزَعَة
457	زَوال
458	زَوَّر
459	زَيَّف
460	زَيْف
461	سَأَل
462	سَجَن
463	سَجِين
464	سَحَب
465	سَحْنَة
466	سَخَّر

No.	One Word Dimensional
467	سَرَق
468	سَرِي
469	سَطْحِيّ
470	سَلْم
471	سَلْبِيّ
472	سَهْو
473	سَيَّل
474	سَيِّء
475	سُخْرِيَّة
476	سُخْط
477	سُدّ
478	سُقُوط
479	سُوء
480	سِجْن
481	شائِك
482	شاحِب
483	شاذّ
484	شاغِر
485	شاقّ
486	شَتّ
487	شَجَب
488	شَحّ
489	شَذّ
490	شَطَب
491	شَطْب
492	شَكا
493	شَكّ
494	شَكَّك
495	شَكْوَى
496	شَنِيع
497	شَهَر
498	شَوَّش
499	شَوَّه
500	شُحّ
501	شِدَّة
502	صادَر
503	صادَم
504	صارَع
505	صارِم
506	صالَح
507	صَحّ
508	صَدّ
509	صَدَّع
510	صَعُب
511	صَعَّد
512	صَعْب
513	صَفَّى
514	صُعُوبَة
515	صِراع
516	ضائِع
517	ضائِقَة
518	ضارّ

No.	One Word Dimensional
519	ضاع
520	ضايَق
521	ضَئِيل
522	ضَحِيَّة
523	ضَخَّم
524	ضَرَر
525	ضَرُورِيّ
526	ضَرّ
527	ضَعِيف
528	ضَغَط
529	ضَغْط
530	ضَلّل
531	ضُعْف
532	ضِدّ
533	طائِش
534	طارِئ
535	طالَب
536	طَرَد
537	طَرْد
538	طَلاق
539	طَمَس
540	ظالِم
541	ظَلّل
542	عائِق
543	عاجِز
544	عار
545	عارَض
546	عاطِل
547	عاق
548	عاقَب
549	عاقِبَة
550	عالِق
551	عانَى
552	عَبَث
553	عَبِث
554	عَجِز
555	عَجْز
556	عَداء
557	عَدُوّ
558	عَدّاء
559	عَدَّل
560	عَرَّض
561	عَرْقَل
562	عَرْقَلَة
563	عَزَل
564	عَزُوف
565	عَشْوائِيّ
566	عَصِيب
567	عَطّل
568	عَقَبَة
569	عَكْس
570	عَلّق

No.	One Word Dimensional
571	عَنِيف
572	عَيْب
573	عُزْلَة
574	عُقُوبَة
575	عُنْف
576	عِبْء
577	عِصْيان
578	عِقاب
579	غاضِب
580	غافَل
581	غالَى
582	غالِي
583	غَرامَة
584	غَرِم
585	غَرِيب
586	غَشّ
587	غَطّى
588	غَفَر
589	غَلِط
590	غَلْطَة
591	غِشّ
592	غِياب
593	فائِت
594	فائِض
595	فات
596	فاجِع
597	فاحِش
598	فادِح
599	فارّ
600	فاسِد
601	فاشِل
602	فدائِي
603	فَجْوَة
604	فَرَض
605	فَزَع
606	فَساد
607	فَسَخ
608	فَسْخ
609	فَشَل
610	فَشِل
611	فَصْل
612	فَضَح
613	فَضِيحَة
614	فَظاظَة
615	فَظّ
616	فَقِير
617	فَلّس
618	فَوْضَوِيّ
619	فُحْش
620	فِقْدان
621	قابِلِيَّة
622	قاسِي

No.	One Word Dimensional
623	قاصِر
624	قاضَى
625	قاطَع
626	قَبِل
627	قَدِيم
628	قَذَف
629	قَذْف
630	قَسَر
631	قَسْر
632	قَسْرِيّ
633	قَسْوَة
634	قَصْر
635	قَطَع
636	قَلَق
637	قَلَّص
638	قَلّل
639	قَمْع
640	قَهْر
641	قَوَّض
642	قَيَّد
643	قُصُور
644	قِصاص
645	قِلّة
646	كاد
647	كاذِب
648	كارِثي
649	كارِثَة
650	كافَح
651	كَئِيب
652	كَبَت
653	كَبَح
654	كَبْح
655	كَتَّم
656	كَذّب
657	كَرِه
658	كَرَّر
659	كَساد
660	كَسَر
661	كَسَل
662	كَسُول
663	كَسْر
664	كَفالَة
665	كَفَّل
666	كِذْب
667	لاأَخْلاقِيّ
668	لاغِي
669	لام
670	لامُبالاة
671	لَطّخ
672	لَها
673	لَوْم
674	مانَع

No.	One Word Dimensional
675	مَأْزِق
676	مَأساة
677	مَأسَوِيّ
678	مَتاعِب
679	مَتْرُوك
680	مَجْرُوح
681	مَحا
682	مَحْبُوس
683	مَحْجُوب
684	مَحْرُوم
685	مَحْصُور
686	مَحْظُور
687	مَحْمَل
688	مَخْزِيّ
689	مَخْفِيّ
690	مَدْعاة
691	مَدْيُون
692	مَذْهُول
693	مَرْفُوض
694	مَزّاح
695	مَزْعَمَة
696	مَزْعُوم
697	مَساءَة
698	مَسْدُود
699	مَسْرُوق
700	مَشَقَّة
701	مَشَى
702	مَشُوش
703	مَشْطُوبٌ
704	مَشْكُوك
705	مَصادَر
706	مَصَفّ
707	مَصِير
708	مَطْرُود
709	مَعْرِض
710	مَعْزُول
711	مَغْرَم
712	مَغْشُوش
713	مَغْلُوط
714	مَفْصُول
715	مَفْقُود
716	مَقْطُوع
717	مَقْعَد
718	مَكِيدَة
719	مَلام
720	مَمْنُوع
721	مَنَع
722	مَنْبُوذ
723	مَنْزُوع
724	مَنْع
725	مَنْقُوض
726	مَهْجُور

No.	One Word Dimensional
727	مَوْقُوف
728	مَوْقِف
729	مَيِّت
730	مُؤاخَذ
731	مُؤامَرَة
732	مُؤَجَّل
733	مُؤَخَّر
734	مُؤْذِي
735	مُؤْسِف
736	مُؤْلِم
737	مُباغِت
738	مُبالَغَة
739	مُبَرِّر
740	مُبْطَل
741	مُبْهَم
742	مُتَآكِل
743	مُتَآمِر
744	مُتَأَخِّر
745	مُتَأَخِّرات
746	مُتَأَهِّب
747	مُتَبايِن
748	مُتَبَلِّد
749	مُتَجَمِّد
750	مُتَحَيِّز
751	مُتَخَلِّف
752	مُتَدَخِّل
753	مُتَدَنِّي
754	مُتَدَهْوِر
755	مُتَذَبْذِب
756	مُتَراجِع
757	مُتَرَدِّد
758	مُتَرَدِّي
759	مُتَساهِل
760	مُتَضارِب
761	مُتَضايِق
762	مُتَضَرِّر
763	مُتَعارِض
764	مُتَعَثِّر
765	مُتَعَجِّل
766	مُتَعَطِّل
767	مُتَعَمَّد
768	مُتَفاقِم
769	مُتَفَشِّي
770	مُتَقاضَى
771	مُتَقَطِّع
772	مُتَقَلِّب
773	مُتَناقِض
774	مُتَهاوِن
775	مُتَهَرِّبٌ
776	مُتَهَوِّر
777	مُتَواطِئٌ
778	مُتَوَتِّر

No.	One Word Dimensional
779	مُتَوَرِّط
780	مُتَوَفَّى
781	مُتَوَقِّف
782	مُتَّهَم
783	مُتْعَب
784	مُثَبِّط
785	مُثَقَّل
786	مُجابَهَة
787	مُجْبَر
788	مُجْحِف
789	مُجْرِم
790	مُجْهَد
791	مُحاكَمَة
792	مُحَذِّر
793	مُحَرَّف
794	مُحَطِّم
795	مُحَيَّر
796	مُحْبِط
797	مُحْتال
798	مُحْتَجَز
799	مُحْتَجّ
800	مُحْتَكِر
801	مُحْرِج
802	مُخادِع
803	مُخالَصَة
804	مُخالَفَة
805	مُخالِف
806	مُخَبَّأَة
807	مُخَفَّض
808	مُخْتَرَق
809	مُخْتَفَى
810	مُخْتَلَس
811	مُخْتَلّ
812	مُخْجِل
813	مُخْطِئ
814	مُدان
815	مُدَمِّر
816	مُدَّعَى
817	مُدَّعِي
818	مُذْنِب
819	مُرابِي
820	مُراوَغَة
821	مُرِيب
822	مُرْبِك
823	مُرْهِق
824	مُزَعْزَع
825	مُزَوَّر
826	مُزَيَّف
827	مُزْعِج
828	مُزْمِن
829	مُسِيء
830	مُسْتاء

No.	One Word Dimensional
831	مُسْتَبْدَل
832	مُسْتَبْعَد
833	مُسْتَحِيل
834	مُسْتَدْعَى
835	مُسْتَهْتَر
836	مُسْتَهْجَنٌ
837	مُشَدِّد
838	مُشْكِلَة
839	مُصاب
840	مُصادَر
841	مُصادَرَة
842	مُصالَحَة
843	مُصَحِّح
844	مُصِيبَة
845	مُضادّ
846	مُضايَقَة
847	مُضَلِّل
848	مُضِرّ
849	مُضْطَرِب
850	مُضْطَرّ
851	مُطالَبَة
852	مُطَوَّل
853	مُعاد
854	مُعادِي
855	مُعارَضَة
856	مُعارِض
857	مُعاقَبَة
858	مُعاقِب
859	مُعاكِس
860	مُعاناة
861	مُعَرْقِل
862	مُعَطِّل
863	مُعَقَّد
864	مُعَلِّق
865	مُعْتَرَف
866	مُعْتَرِض
867	مُعْتَقَل
868	مُعْتَلّ
869	مُعْسِر
870	مُغالاة
871	مُغالِي
872	مُغْرِض
873	مُغْلَق
874	مُفاجِئ
875	مُفْتَقِر
876	مُفْرِط
877	مُفْسِد
878	مُفْشَى
879	مُفْلِس
880	مُقاضاة
881	مُقاطَعَة
882	مُقَصِّر

No.	One Word Dimensional
883	مُقَلِّص
884	مُقَيِّد
885	مُقْلِق
886	مُكَلِّف
887	مُلِحّ
888	مُلْتَبِس
889	مُلْغَى
890	مُمْتَعِض
891	مُنافِس
892	مُناقِض
893	مُناهِض
894	مُناوِئ
895	مُنَفِّر
896	مُنْتَزَع
897	مُنْتَقِم
898	مُنْتَهَك
899	مُنْحَدَر
900	مُنْحَرِف
901	مُنْحَلّ
902	مُنْخَفِض
903	مُنْزَعِج
904	مُنْسَحِب
905	مُنْشَقّ
906	مُنْفَصِل
907	مُنْقَطِع
908	مُنْكَمِش
909	مُنْهار
910	مُهِين
911	مُهْدَر
912	مُهْمَل
913	مُواجَهَة
914	مِحْجَم
915	مِحْنَة
916	مِحْوَرِيّ
917	نازَع
918	ناضَل
919	نافَس
920	ناقَض
921	ناقِص
922	نَأى
923	نَبَذ
924	نَبَّه
925	نَحَل
926	نَحَّى
927	نَدَّد
928	نَدْرَة
929	نَزَع
930	نَصَّف
931	نَفَر
932	نَفَى
933	نَفْرَة
934	نَقَض

No.	One Word Dimensional
935	نَقْص
936	نَقْض
937	نَكْسَة
938	نُضُوب
939	نُقْصان
940	نِزاع
941	هابِط
942	هاجَم
943	هارِب
944	هَبَط
945	هَجَر
946	هَجَم
947	هَجْر
948	هَدَم
949	هَدّام
950	هَدَّد
951	هَدْم
952	هَزِيل
953	هَزِيمَة
954	هَشّ
955	هَفْوَة
956	هَلَع
957	هُبُوط
958	واقِعَة
959	وَبَّخ
960	وَخِيم
961	وَشِيك
962	وَفاة
963	وَقاحَة
964	وَقَح
965	وَقْف
966	وَهِم
967	وِقائِيّ
968	اِتَّهَم
969	اِتِّهام
970	اِحْتاج
971	اِحْتال
972	اِحْتَجَز
973	اِحْتَرَز
974	اِحْتَقَر
975	اِحْتَكَر
976	اِحْتِجاج
977	اِحْتِجاز
978	اِحْتِراز
979	اِحْتِراس
980	اِحْتِقار
981	اِحْتِكار
982	اِحْتِيال
983	اِخْتَفَى
984	اِخْتَلَس
985	اِخْتَلَف
986	اِخْتِراق

No.	One Word Dimensional
987	ٱخْتِفاء
988	ٱخْتِلاس
989	ٱخْتِلاف
990	ٱخْتِلال
991	ٱدَّعَى
992	ٱدِّعاء
993	ٱرْتاب
994	ٱرْتَكَب
995	ٱرْتِباك
996	ٱرْتِكاب
997	ٱزْدِراء
998	ٱسْتَبْعَد
999	ٱسْتَبْقَى
1000	ٱسْتَجْوَب
1001	ٱسْتَدْعَى
1002	ٱسْتَفَزّ
1003	ٱسْتَفْحَل
1004	ٱسْتَقال
1005	ٱسْتَقْصَى
1006	ٱسْتَنْزَف
1007	ٱسْتَنْفَد
1008	ٱسْتَنْكَر
1009	ٱسْتَهْجَن
1010	ٱسْتَهْزَأ
1011	ٱسْتَوْقَف
1012	ٱسْتَوْلَى
1013	ٱسْتِبْدال
1014	ٱسْتِحالَة
1015	ٱسْتِخْفاف
1016	ٱسْتِدْعاء
1017	ٱسْتِرْضاء
1018	ٱسْتِسْلام
1019	ٱسْتِغْلال
1020	ٱسْتِفْزاز
1021	ٱسْتِفْسار
1022	ٱسْتِقالَة
1023	ٱسْتِقْصاء
1024	ٱسْتِنْزاف
1025	ٱسْتِنْفار
1026	ٱسْتِنْكار
1027	ٱسْتِهْجان
1028	ٱسْتِهْزاء
1029	ٱسْتِياء
1030	ٱسْتِيلاء
1031	ٱشْتَبَه
1032	ٱشْتَكَى
1033	ٱشْتِباه
1034	ٱصْطِدام
1035	ٱضْطَرَب
1036	ٱضْطَرّ
1037	ٱضْطِراب
1038	ٱضْمَحَلّ

No.	One Word Dimensional
1039	ٱِعْتَدَى
1040	ٱِعْتَرَض
1041	ٱِعْتَرَف
1042	ٱِعْتَزَل
1043	ٱِعْتَقَل
1044	ٱِعْتَمّ
1045	ٱِعْتِداء
1046	ٱِعْتِراض
1047	ٱِعْتِراف
1048	ٱِعْتِزال
1049	ٱِعْتِقال
1050	ٱِعْتِلال
1051	ٱِغْتَصَب
1052	ٱِفْتَرَى
1053	ٱِفْتَقَر
1054	ٱِفْتِراء
1055	ٱِفْتِقار
1056	ٱِقْتَحَم
1057	ٱِقْتَرَف
1058	ٱِقْتِحام
1059	ٱِقْتِراف
1060	ٱِكْتَشَف
1061	ٱِكْتِراث
1062	ٱِلْتَمَس
1063	ٱِلْتِفاف
1064	ٱِلْتِماس
1065	ٱِمْتَنَع
1066	ٱِمْتِعاض
1067	ٱِمْتِناع
1068	ٱِنْتَزَع
1069	ٱِنْتَقَد
1070	ٱِنْتَقَص
1071	ٱِنْتَقَم
1072	ٱِنْتَهَز
1073	ٱِنْتَهَك
1074	ٱِنْتِزاع
1075	ٱِنْتِقاد
1076	ٱِنْتِقاص
1077	ٱِنْتِقام
1078	ٱِنْتِكاس
1079	ٱِنْتِهاز
1080	ٱِنْتِهازِيّ
1081	ٱِنْتِهاك
1082	ٱِنْحَدَر
1083	ٱِنْحَرَف
1084	ٱِنْحِدار
1085	ٱِنْحِراف
1086	ٱِنْحِسار
1087	ٱِنْخَفَض
1088	ٱِنْخِفاض
1089	ٱِنْزَعَج
1090	ٱِنْزِعاج

No.	One Word Dimensional
1091	ٱِنْزِلاق
1092	ٱِنْسَحَب
1093	ٱِنْشَقّ
1094	ٱِنْضِباط
1095	ٱِنْعِدام
1096	ٱِنْفَصَل
1097	ٱِنْفِصال
1098	ٱِنْقَضَى
1099	ٱِنْقَطَع
1100	ٱِنْقِباض
1101	ٱِنْقِطاع
1102	ٱِنْكِماش
1103	ٱِنْهار
1104	ٱِنْهَزَم
1105	ٱِنْهِيار

Table A2. (b-3.ii) Negative Arabic Two Words Dimensional (*N=756*)

No.	Two Words Dimensional
1	أَخْطَأَ فَهْم
2	أَخْلَى مَسْؤُولِيَّة
3	أداء ضَعِيف
4	أَساء إِدارَة
5	أَساء تَدْبِير
6	أَساء تَسْمِيَة
7	أَساء تَصَرُّف
8	أَساء تَطْبِيق
9	أَساء تَفْسِير
10	أَساء تَقْدِير
11	أَساء حُكْم
12	أَساء سُمْعَة
13	أَساء فَهْم
14	أَساء مُعامَلَة
15	أَساء ٱِسْتِخْدام
16	أَساء ٱِسْتِعْمال
17	أَضْعَف سُمْعَة
18	أَعاد تَأْكِيد
19	أَعاد تَخْصِيص
20	أَعاد تَعْيِين
21	أَعاد تَفاوُض
22	أَعاد تَكْلِيف
23	أَعاد تَنْظِيم
24	أَعاد تَوْزِيع
25	أَعاد رِبْح
26	أَعاد سَداد
27	أَعاد هَيْكَلَة
28	أَعْلَى خُطُورَة
29	أَعْلَى مُخاطَرَة
30	أَفاض عَن
31	أَفْقَد أَهْلِيَّة
32	أَفْقَد مِصْداقِيَّة
33	أَكْثَر خُطُورَة
34	أَكْثَر سُوء
35	أَكْثَر شِدَّة
36	أَكْثَر ضُعْف
37	أَكْثَر قَسْوَة
38	أَكْثَر مُخاطَرَة
39	أَلْزَم دَفْع
40	أَلْغَى إِدْراج
41	أَمْر قَضائِيّ
42	أُجْرَ زَهِيد
43	إِجْراء مُضادّ
44	إِخْلاء مَسْؤُولِيَّة
45	إِزالَة تُهْمَة
46	إِساءَة إِدارَة
47	إِساءَة تَصَرُّف
48	إِساءَة تَطْبِيق
49	إِساءَة تَعامُل
50	إِساءَة تَفْسِير

51	إِساءَة تَقْدِير
52	إِساءَة حُكْم
53	إِساءَة سُلُوك
54	إِساءَة فَهْم
55	إِساءَة مُعامَلَة
56	إِساءَة ٱِسْتِخْدام
57	إِساءَة ٱِسْتِعْمال
58	إِسْتراتِيجِيَّة مُضادّ
59	إِصْدار بَراءَة
60	إِعادَة إِجْبارِيّ
61	إِعادَة تَخْصِيص
62	إِعادَة تَعْيِين
63	إِعادَة تَفاوُض
64	إِعادَة تَقْدِير
65	إِعادَة تَقْيِيم
66	إِعادَة تَنْظِيم
67	إِعادَة سَداد
68	إِعادَة هَيْكَلَة
69	إِعْلان بَراءَة
70	إِعْلان كاذِب
71	إِغاثَة مالِيّ
72	إِلْغاء أَهْلِيَّة
73	إِنْتاج زائِد
74	إِنْتاج مُفْرِط
75	إِنْذار قَضائِيّ
76	إِهْمال إِدارِيّ
77	إِهْمال مِهْنِيّ
78	إِيقاف أَمْنِيّ
79	الأَكْثَر بُطْء
80	الأَكْثَر رُكُود
81	التَنَمُّر إِلِكْترُونِيّ
82	بَرِيد عَشْوائِيّ
83	بَرِيد مُزْعِج
84	بَعِيد مَنال
85	بَيان خاطِئ
86	بَيان كاذِب
87	بَيان مَغْلُوط
88	بَيان مُضَلِّل
89	بِلا أَساس
90	بِلا تَأمِين
91	بِلا تَعْوِيض
92	بِلا داعِي
93	بِلا سَبَب
94	بِلا قِيمَة
95	بِلا كَفاءَة
96	بِلا مُبالاة
97	بِلا مُبَرِّر
98	تارِيخ رَجْعِيّ
99	تارِيخ مُسْبَق
100	تَأَخُّر سَداد
101	تَأْوِيل خاطِئ
102	تَبْيِيض مال
103	تَجاوُز أَمْر

104	تَجاوُز قانُون
105	تَحَيَّز ضِدّ
106	تَحْمِيل زائِد
107	تَخَلّى عَن
108	تَخْفِيض سِعْر
109	تَخْفِيض قِيمَة
110	تَدْبِير خاطِئ
111	تَدْبِير مُضادّ
112	تَدْبِير مُواجَهَة
113	تَرْتِيب خَطَأ
114	تَسْعِير خاطِئ
115	تَسْمِيَة خاطِئ
116	تَشْوِيه سُمْعَة
117	تَصْرِيح خاطِئ
118	تَصْنِيف خاطِئ
119	تَعامُل سَيِّء
120	تَعَرَّض ٱعْتِداء
121	تَفْسِير خاطِئ
122	تَقْدِير خاطِئ
123	تَقْصِير إدارِيّ
124	تَقْلِيل قِيمَة
125	تَمّ إلْغاء
126	تَمّ تَبْرِئَة
127	تَمّ حَظْر
128	تَمّ خَطَر
129	تَمّ رَفْض
130	تَمّ مُقاضاة
131	تَمّ مُقاطَعَة
132	تَمّ ٱسْتِدْعاء
133	تَنازَل عَن
134	تَوْصِيف خاطِئ
135	جَرَى ٱسْتِدْعاء
136	جَرِيمَة إلِكْتْرُونِيّ
137	جَرِيمَة رَقَمِيّ
138	حَبَس رَهْن
139	حَجْب مَعْلُومَة
140	حَسَب ٱدِّعاء
141	حُكْم خاطِئ
142	حُمُولَة زائِد
143	خارِج خِدْمَة
144	خارِج سَيْطَرَة
145	خَصْم دَيْن
146	خَفَّض قِيمَة
147	خَلا ٱسْتِقْرار
148	خَيْبَة أَمَل
149	دَعْوَة مَحْكَمَة
150	دَعْوَى قَضائِيّ
151	دَعْوَى مُضادّ
152	دَفَع زِيادَة
153	دَفْع زائِد
154	دَفْع مُنْخَفِض
155	دَيْن مَعْدُوم
156	دَيْن مُعَلَّق

157	دُون إِدْراك
158	دُون تَأْمِين
159	دُون تَخْطِيط
160	دُون تَرْخِيص
161	دُون تَعْوِيض
162	دُون دَلِيل
163	دُون دِرايَة
164	دُون رُخْصَة
165	دُون سَبَب
166	دُون عَلِم
167	دُون عُذْر
168	دُون قَصَد
169	دُون مَعْرِفَة
170	دُون مُبَرِّر
171	دُون مُسْتَوَى
172	رَسْم زائِد
173	زَعَم أَنَّ
174	زَعْزَع ٱِسْتِقْرار
175	زِيادَة تَحْمِيل
176	سابِق أَوان
177	سَداد مُنْخَفِض
178	سَرِيع تَأَثُّر
179	سَيِّء سُمْعَة
180	سُمْعَة سَيِّء
181	سُوء إِدارَة
182	سُوء تَدْبِير
183	سُوء تَسْعِير
184	سُوء تَصَرُّف
185	سُوء تَعامُل
186	سُوء تَفاهُم
187	سُوء تَقْدِير
188	سُوء تَوْجِيه
189	سُوء حَظّ
190	سُوء حُكْم
191	سُوء سُلُوك
192	سُوء فَهْم
193	سُوء مُعامَلَة
194	سُوء نِيَّة
195	سُوء ٱِتِّصال
196	سُوء ٱِسْتِخْدام
197	سُوء ٱِسْتِعْمال
198	شَحّ سُيُولَة
199	شَطْب دِين
200	شَكْل إِجْرامِيّ
201	شَكْل إِلْزامِيّ
202	شَكْل بَشِع
203	شَكْل بَطِيء
204	شَكْل تَعَسُّفِيّ
205	شَكْل جائِر
206	شَكْل جَدَل
207	شَكْل جَسِيم
208	شَكْل جِدِّيّ
209	شَكْل حادّ

210	شَكْل حَرَج
211	شَكْل خادِع
212	شَكْل خاطِئ
213	شَكْل خَطِير
214	شَكْل رَدِيء
215	شَكْل سَلْبِيّ
216	شَكْل سَيِّء
217	شَكْل شاذّ
218	شَكْل شاقّ
219	شَكْل شَنِيع
220	شَكْل صَعْب
221	شَكْل ضارّ
222	شَكْل ضَرُورِيّ
223	شَكْل ضَعِيف
224	شَكْل طائِش
225	شَكْل ظالِم
226	شَكْل عَكْسِيّ
227	شَكْل عَلَنِيّ
228	شَكْل عَنِيف
229	شَكْل فادِح
230	شَكْل فاسِد
231	شَكْل فاشِل
232	شَكْل قاتِل
233	شَكْل كاذِب
234	شَكْل كارِثِي
235	شَكْل مَأْسَوِيّ
236	شَكْل مَخْزِيّ
237	شَكْل مَرْفُوض
238	شَكْل مَزْعُوم
239	شَكْل مَغْلُوط
240	شَكْل مَنْقُوص
241	شَكْل مُؤْذِي
242	شَكْل مُؤْسِف
243	شَكْل مُباغِت
244	شَكْل مُتَأَخِّر
245	شَكْل مُتَذَبْذِب
246	شَكْل مُتَضارِب
247	شَكْل مُتَعَجِّل
248	شَكْل مُتَعَمَّد
249	شَكْل مُتَفَشِّي
250	شَكْل مُتَقَطِّع
251	شَكْل مُتَقَلِّب
252	شَكْل مُتَناقِض
253	شَكْل مُتَهاوِن
254	شَكْل مُتَهَوِّر
255	شَكْل مُجْحِف
256	شَكْل مُحَيِّر
257	شَكْل مُحْبِط
258	شَكْل مُخادِع
259	شَكْل مُخْطِئ
260	شَكْل مُدَمِّر
261	شَكْل مُذْنِب
262	شَكْل مُرِيب

263	شَكْل مُرْبِك
264	شَكْل مُزَيَّف
265	شَكْل مُسِيء
266	شَكْل مُصْطَنَع
267	شَكْل مُضَلِّل
268	شَكْل مُعاكِس
269	شَكْل مُعَقَّد
270	شَكْل مُفاجِئ
271	شَكْل مُفْرِط
272	شَكْل مُلِحّ
273	شَكْل مُهِين
274	شَكْل ناقِص
275	شَكْل هَشّ
276	شَكْل اِحْتِيال
277	شَكْل اِزْدِراء
278	شَكْل اِنْتِهازِيّ
279	شَهادَة زُور
280	شَوَّه سُمْعَة
281	صَدَر بَراءَة
282	صَدَر حُكْم
283	صَعْب قِراءَة
284	صُدُور حُكْم
285	صُعُوبَة تَحْصِيل
286	صُورَة إِجْرامِيّ
287	صُورَة بَطِيء
288	صُورَة جَدَل
289	صُورَة حادّ
290	صُورَة حَرِج
291	صُورَة خاطِئ
292	صُورَة خَطِير
293	صُورَة سَلْبِيّ
294	صُورَة سَيِّء
295	صُورَة شاذّ
296	صُورَة شاقّ
297	صُورَة صَعْب
298	صُورَة ضارّ
299	صُورَة ضَرُورِيّ
300	صُورَة عَكْسِيّ
301	صُورَة فادِح
302	صُورَة فاسِد
303	صُورَة مَغْلُوط
304	صُورَة مُؤْذِي
305	صُورَة مُؤْسِف
306	صُورَة مُباغِت
307	صُورَة مُتَأَخِّر
308	صُورَة مُتَعَجِّل
309	صُورَة مُتَعَمَّد
310	صُورَة مُتَقَلِّب
311	صُورَة مُتَهَوِّر
312	صُورَة مُحَيِّر
313	صُورَة مُحْبِط
314	صُورَة مُخادِع
315	صُورَة مُذْنِب

316	صُورَة مُرْبِك
317	صُورَة مُسِيء
318	صُورَة مُضَلِّل
319	صُورَة مُضِرّ
320	صُورَة مُعاكِس
321	صُورَة مُفاجِئ
322	صُورَة مُفْرِط
323	صُورَة اِحْتِيال
324	صُورَة اِزْدِراء
325	صُورَة اِصْطِناعِيّ
326	ضارّ سُمْعَة
327	ضَعِيف أداء
328	ضَعِيف تَمْوِيل
329	ضُعْف أداء
330	ضِدّ مُنافَسَة
331	ضِدّ اِحْتِكار
332	طاقَة زائِد
333	طَرِيق خَطَأ
334	طَرِيق مَسْدُود
335	طَرِيقَة جَدَل
336	طَرِيقَة حادّ
337	طَرِيقَة حَرِج
338	طَرِيقَة خاطِئ
339	طَرِيقَة خَطَر
340	طَرِيقَة سَطْحِيّ
341	طَرِيقَة سَلْبِيّ
342	طَرِيقَة شاذّ
343	طَرِيقَة شاقّ
344	طَرِيقَة صَعْب
345	طَرِيقَة ضارّ
346	طَرِيقَة عَكْسِيّ
347	طَرِيقَة فادِح
348	طَرِيقَة فاسِد
349	طَرِيقَة مَغْلُوط
350	طَرِيقَة مُؤْذِي
351	طَرِيقَة مُؤْسِف
352	طَرِيقَة مُباغِت
353	طَرِيقَة مُتَأَخِّر
354	طَرِيقَة مُتَعَمَّد
355	طَرِيقَة مُتَهَوِّر
356	طَرِيقَة مُحَيِّر
357	طَرِيقَة مُحْبِط
358	طَرِيقَة مُخادِع
359	طَرِيقَة مُرْبِك
360	طَرِيقَة مُزَيَّف
361	طَرِيقَة مُسِيء
362	طَرِيقَة مُضَلِّل
363	طَرِيقَة مُعاكِس
364	طَرِيقَة مُفاجِئ
365	طَرِيقَة اِحْتِيال
366	طَرِيقَة اِزْدِراء
367	عالِي تَأَثُّر
368	عَدَم أمانَة

369	عَدَم أَهْلِيَّة
370	عَدَم إِخْلاص
371	عَدَم إِفْصاح
372	عَدَم تَجْدِيد
373	عَدَم تَرْكِيز
374	عَدَم تَفْضِيل
375	عَدَم تَناسُب
376	عَدَم تَناسُق
377	عَدَم تَوازُن
378	عَدَم تَوافُق
379	عَدَم تَوَفُّر
380	عَدَم ثَبات
381	عَدَم جَداء
382	عَدَم جَدارَة
383	عَدَم خِبْرَة
384	عَدَم دَفْع
385	عَدَم دِقَّة
386	عَدَم راحَة
387	عَدَم رَغْبَة
388	عَدَم رِضَى
389	عَدَم سَداد
390	عَدَم سَماح
391	عَدَم سُيُولَة
392	عَدَم شَرْعِيَّة
393	عَدَم صِحَّة
394	عَدَم صِدْق
395	عَدَم فَعّالِيَّة
396	عَدَم قُدْرَة
397	عَدَم كَفاءَة
398	عَدَم كِفايَة
399	عَدَم مَشْرُوعِيَّة
400	عَدَم مَعْقُولِيَّة
401	عَدَم مُساواة
402	عَدَم مُطابَقَة
403	عَدَم مُلاءَمَة
404	عَدَم مُوافَقَة
405	عَدَم نَضْج
406	عَدَم واقِعِيَّة
407	عَدَم وَفاء
408	عَدَم وَلاء
409	عَدَم اِتِّساق
410	عَدَم اِسْتِجابَة
411	عَدَم اِسْتِحْسان
412	عَدَم اِسْتِحْقاق
413	عَدَم اِسْتِقْرار
414	عَدَم اِكْتِراث
415	عَدَم اِلْتِزام
416	عَدَم اِمْتِثال
417	عَدَم اِنْتِباه
418	عَدَم اِنْتِظام
419	عَدَم اِنْتِماء
420	عَدَم اِنْسِجام
421	عَدَم اِهْتِمام

422	عَدِيم أَهْلِيَّة
423	عَدِيم جَداء
424	عَدِيم جَدارَة
425	عَدِيم خِبْرَة
426	عَدِيم فائِدَة
427	عَدِيم كَفاءَة
428	عُرْضَة مُقاضاة
429	عُرْضَة إِتِّهام
430	عِبْء زائِد
431	غَسِيل مال
432	غَيْر آمِن
433	غَيْر أَخْلاقِيّ
434	غَيْر أَمِين
435	غَيْر تَنافُس
436	غَيْر ثابِت
437	غَيْر جَذّاب
438	غَيْر حاسِم
439	غَيْر دَقِيق
440	غَيْر رائِج
441	غَيْر راضِي
442	غَيْر شَرِيف
443	غَيْر صادِق
444	غَيْر صالِح
445	غَيْر صَحِيح
446	غَيْر ضَرُورِيّ
447	غَيْر طَبِيعِيّ
448	غَيْر عادِل
449	غَيْر عادِيّ
450	غَيْر عَمَلِيّ
451	غَيْر فَعّال
452	غَيْر قادِر
453	غَيْر قاطِع
454	غَيْر قانُونِيّ
455	غَيْر كافِي
456	غَيْر كُفُوء
457	غَيْر لائِق
458	غَيْر لازِم
459	غَيْر مَألُوف
460	غَيْر مَأمُون
461	غَيْر مَأهُول
462	غَيْر مَتِين
463	غَيْر مَجْد
464	غَيْر مَجْدُول
465	غَيْر مَحْسُوب
466	غَيْر مَحْلُول
467	غَيْر مَدْفُوع
468	غَيْر مَرَضِيّ
469	غَيْر مَرْصُود
470	غَيْر مَرْغُوب
471	غَيْر مَسْمُوح
472	غَيْر مَشْرُوع
473	غَيْر مَعْرُوف
474	غَيْر مَعْقُول

475	غَيْر مَعْلُوم
476	غَيْر مَقْبُول
477	غَيْر مَقْرُوء
478	غَيْر مَقْصُود
479	غَيْر مَكْشُوف
480	غَيْر مَلام
481	غَيْر مَنْطِقِيّ
482	غَيْر مَوْثُوق
483	غَيْر مَوْثِق
484	غَيْر مَوْجُود
485	غَيْر مُؤاتِي
486	غَيْر مُؤَكِّدٍ
487	غَيْر مُؤَهَّل
488	غَيْر مُؤْمِن
489	غَيْر مُباع
490	غَيْر مُبالِي
491	غَيْر مُبَرِّر
492	غَيْر مُتاح
493	غَيْر مُتَجانِس
494	غَيْر مُتَساوِي
495	غَيْر مُتَطابِق
496	غَيْر مُتَعَمَّد
497	غَيْر مُتَكافِئ
498	غَيْر مُتَمَرِّس
499	غَيْر مُتَناسِب
500	غَيْر مُتَوازِن
501	غَيْر مُتَوَقَّع
502	غَيْر مُتَّسِق
503	غَيْر مُثْمِر
504	غَيْر مُحَدَّد
505	غَيْر مُحَصِّل
506	غَيْر مُخْلِص
507	غَيْر مُدْرِك
508	غَيْر مُرَخَّص
509	غَيْر مُرِيح
510	غَيْر مُرْبِح
511	غَيْر مُسْتَجِيب
512	غَيْر مُسْتَحَبّ
513	غَيْر مُسْتَحْسَن
514	غَيْر مُسْتَدام
515	غَيْر مُسْتَقِرّ
516	غَيْر مُشَجِّع
517	غَيْر مُصَحِّح
518	غَيْر مُصَرَّح
519	غَيْر مُصَفَّى
520	غَيْر مُطَابِقٌ
521	غَيْر مُعالِج
522	غَيْر مُعَدَّل
523	غَيْر مُعْتَمَد
524	غَيْر مُعْلَن
525	غَيْر مُغَطًّى
526	غَيْر مُفَضَّل
527	غَيْر مُفِيد

528	غَيْر مُقْنِع
529	غَيْر مُكْتَشِف
530	غَيْر مُكْتَمَل
531	غَيْر مُلْفِت
532	غَيْر مُمَوَّل
533	غَيْر مُناسِب
534	غَيْر مُنْتَظِم
535	غَيْر مُنْتِج
536	غَيْر مُنْجَز
537	غَيْر مُنْسَجِم
538	غَيْر مُنْصِف
539	غَيْر مُنْضَبِط
540	غَيْر مُهْتَمّ
541	غَيْر ناجِح
542	غَيْر ناضِج
543	غَيْر واثِق
544	غَيْر واقِعِيّ
545	غَيْر وَعَى
546	غَيْر وُدِّيّ
547	غَيْر ٱعْتِياد
548	فائِض إِنْتاج
549	فائِض تَمْوِين
550	فائِض طاقَة
551	فائِض عَرْض
552	فائِض قُدْرَة
553	فاقِد أَهْلِيَّة
554	فَرْض حَظْر
555	فَشَل إِدارِيّ
556	فَكّ ٱرْتِباط
557	فِقْدان أَهْلِيَّة
558	فِقْدان ثِقَة
559	قابِل تَبْرِير
560	قَصْر أَداء
561	قَصْر إِنْتاج
562	قَطْع صِلَة
563	قَطْع عَلاقَة
564	قَلِيل خِبْرَة
565	قَلّل قِيمَة
566	قُدْرَة زائِد
567	قُرْص إِلِكْتْرُونِيّ
568	قِبَل أَوان
569	قِبَل مُحاكَمَة
570	قِسْط مُتَأَخِّر
571	قِلّة خِبْرَة
572	كَفاءَة مالِيّ
573	كَما زَعَم
574	لا أَقَرّ
575	لا سَمَح
576	لا عَوَّض
577	لا مُبالِي
578	لا وافَق
579	لا ٱتَّفَق
580	لا ٱسْتَحْسَن

581	لا اِسْتَطاع
582	لائِحَة اِتّهام
583	لَم اِسْتَحْسَن
584	لَيس عادِل
585	لَيس عَمَلِيّ
586	لَيس مُبالِي
587	لَيس مُبَرّر
588	لَيس مُنْسَجِم
589	لَيس واقِعِيّ
590	مَبْلَغ مُسْتَحِقّ
591	مَحَلّ تَساؤُل
592	مَحَلّ جَدَل
593	مَحَلّ جِدال
594	مَحَلّ خِلاف
595	مَحَلّ شَكّ
596	مَحَلّ نِزاع
597	مَحْدُود قُدْرَة
598	مَحْكُوم عَلَى
599	مَشْكُوك بِ
600	مَشْكُوك فِي
601	مَع أسَف
602	مَعْلُومَة خاطِئ
603	مَعْلُومَة مَغْلُوط
604	مَعْلُومَة مُضَلِّل
605	مَنْفَى قانُون
606	مَوْضِع تَساؤُل
607	مَوْضِع خِلاف
608	مَوْضِع شَكّ
609	مُبالَغ فِي
610	مُتَأَخِّر عَن
611	مُتَعَدِّي عَلَى
612	مُتَعَذِّر إصْلاح
613	مُتَنازَع عَلَى
614	مُتَنازِل عَن
615	مُتَنافِس عَلَى
616	مُثِير جَدَل
617	مُثِير خِلاف
618	مُثِير نِزاع
619	مُثِير اِشْمِئْزاز
620	مُجْرِم إلِكْترُونِيّ
621	مُحارَبَة اِحْتِكار
622	مُحاكَمَة باطِل
623	مُحاكَمَة مُلْغَى
624	مُخالِف خُلْق
625	مُخالِف قانُون
626	مُخْتَرَق إلِكْترُونِيّ
627	مُخْتَلِف عَلَى
628	مُدَّعَى عَلَى
629	مُذَكّرَة اِسْتِدْعاء
630	مُسَمَّى خَطَأ
631	مُسْتَحِيل تَحْصِيل
632	مُسْتَحِيل تَسْلِيم
633	مُسْتَغْنَى عَن

634	مُشَكِّك بِ
635	مُشْتَبَه بِ
636	مُصَنَّف خَطَأ
637	مُضادّ مُنافَسَة
638	مُضادّ اِحْتِكار
639	مُضايَقَة إِلِكْترُونِيّ
640	مُطالَبَة مُضادّ
641	مُعامَلَة سَيِّء
642	مُغالِي بِ
643	مُفاوَضَة جَدِيد
644	مُكافَحَة اِحْتِكار
645	مُلْغَى أَهْلِيَّة
646	مُنافِي خُلْق
647	مُناقِض خُلْق
648	مُناهِض تَنافُس
649	مُناهِض اِحْتِكار
650	مُنْخَفِض قِيمَة
651	مِلايَة مالِيّ
652	ناقِص إِنْتاج
653	نَحْو إِجْرامِيّ
654	نَحْو إِلْزامِيّ
655	نَحْو بَشِع
656	نَحْو بَطِيء
657	نَحْو تَعَسُّفِيّ
658	نَحْو جائِر
659	نَحْو جَدَل
660	نَحْو جَسِيم
661	نَحْو حادّ
662	نَحْو حَرَج
663	نَحْو خادِع
664	نَحْو خاطِئ
665	نَحْو خَطِير
666	نَحْو رَدِيء
667	نَحْو سَطْحِيّ
668	نَحْو سَلْبِيّ
669	نَحْو سَيِّء
670	نَحْو شاذّ
671	نَحْو شاقّ
672	نَحْو شَنِيع
673	نَحْو صَعْب
674	نَحْو ضارّ
675	نَحْو ضَرُورِيّ
676	نَحْو ضَعِيف
677	نَحْو طائِش
678	نَحْو ظالِم
679	نَحْو عَكْسِيّ
680	نَحْو عَنِيف
681	نَحْو فادِح
682	نَحْو فاسِد
683	نَحْو قاتِل
684	نَحْو كارِثي
685	نَحْو مَأْسَوِيّ
686	نَحْو مَخْزِيّ

687	نَحْو مَرْفُوض
688	نَحْو مَغْلُوط
689	نَحْو مُؤْذِي
690	نَحْو مُؤْسِف
691	نَحْو مُباغِت
692	نَحْو مُتَأَخِّر
693	نَحْو مُتَذَبْذِب
694	نَحْو مُتَضارِب
695	نَحْو مُتَعَجِّل
696	نَحْو مُتَعَمَّد
697	نَحْو مُتَفَشِّي
698	نَحْو مُتَقَطِّع
699	نَحْو مُتَناقِض
700	نَحْو مُتَهاوِن
701	نَحْو مُتَهَوِّر
702	نَحْو مُحَيِّر
703	نَحْو مُحْبِط
704	نَحْو مُخادِع
705	نَحْو مُخْطِئ
706	نَحْو مُدَمِّر
707	نَحْو مُذْنِب
708	نَحْو مُرْبِك
709	نَحْو مُزَيَّف
710	نَحْو مُسِيء
711	نَحْو مُصْطَنَع
712	نَحْو مُضَلِّل
713	نَحْو مُعاكِس
714	نَحْو مُعَقَّد
715	نَحْو مُفاجِئ
716	نَحْو مُفْرِط
717	نَحْو مُلِحّ
718	نَحْو مُهِين
719	نَحْو اِحْتِيال
720	نَحْو اِزْدِراء
721	نَحْو اِنْتِهازِيّ
722	نَزْع مِلْكِيَّة
723	نَقص قِيمَة
724	نَقَل مِلْكِيَّة
725	نَقْص إِنْتاج
726	نَقْص سُيُولَة
727	نَقْل مِلْكِيَّة
728	هَجْمَة مَعْلُوماتِيّ
729	هُجُوم إِلِكْتِرُونِيّ
730	هُجُوم مَعْلُومَة
731	وَتِيرَة بَطِيء
732	وَجَّه اِتِّهام
733	وَسِيلَة مُضادّ
734	اِحْتِيال مالِيّ
735	اِخْتِلال تَوازُن
736	اِدِّعاء مُضادّ
737	اِسْتَدْعَى مَحْكَمَة
738	اِسْتَرَدّ مِلْكِيَّة
739	اِسْتَغْنَى عَن

740	اِسْتِدْعاء قَضائِيّ
741	اِسْتِرْجاع مَبْلَغ
742	اِسْتِرْجاع مِلْكِيَّة
743	اِسْتِرْداد مال
744	اِسْتِرْداد مَدْفُوع
745	اِسْتِرْداد مِلْكِيَّة
746	اِسْتِعادَة مال
747	اِسْتِعادَة مِلْكِيَّة
748	اِسْتِغْلال خاطِئ
749	اِسْتِغْلال مالِيّ
750	اِسْتِقْرار مالِيّ
751	اِنْتِهازِيّ مالِيّ
752	اِنْتِهاك قانُون
753	اِنْخِفاض سُيُولَة
754	اِنْخِفاض قِيمَة
755	اِنْعِدام تَوازُن
756	اِنْعِدام اِسْتِقْرار

Table A2. (b-3.iii) Negative Arabic Three Words Dimensional (*N=260*)

No.	Three Words Dimensional
1	أَجْبَر عَلَى إِعادَة
2	أَخْطَأَ فِي تَسْعِير
3	أَخْطَأَ فِي تَصْنِيف
4	أَخْطَأَ فِي تَطْبِيق
5	أَخْطَأَ فِي تَقْدِير
6	أَخْطَأَ فِي تَقْسِيم
7	أَخْطَأَ فِي حُكْم
8	أَخْطَأَ فِي حِساب
9	أَداء دُون تَوَقُّع
10	أَداء دُون مُسْتَوَى
11	أَدَّى دُون مُسْتَوَى
12	أَعْلَن شَكْل خاطِئ
13	إِدْلاء شَهادَة كاذِب
14	إِفادَة غَيْر صَحِيح
15	إِفْراط فِي إِنْتاج
16	إِفْراط فِي بِناء
17	إِنْتاج غَيْر كافِي
18	التَنَمُّر عَبْر إِنْتِرْنِت
19	بالَغ فِي بِناء
20	بالَغ فِي تَثْمِين
21	بالَغ فِي تَقْدِير
22	بالَغ فِي تَقْيِيم
23	بِنْيَة إِلْحاق ضَرَر
24	تَأَخَّر عَن سَداد
25	تَأْخِير فِي دَفْع
26	تَجاوَز فِي بِناء
27	تَجْرِيد مِن أَهْلِيَّة
28	تَخَلَّى عَن رِبْح
29	تَخَلُّف عَن دَفْع
30	تَخَلُّف عَن سَداد
31	تَخْفِيف مِن أَهَمِّيَّة
32	تَرْتِيب غَيْر دَقِيق
33	تَصْرِيح غَيْر صَحِيح
34	تَعَذَّر وُصُول إِلَى
35	تَقْسِيم غَيْر صَحِيح
36	تَقْصِير فِي أَداء
37	تَقْصِير فِي سَداد
38	تَمّ هُجُوم عَلَى
39	جَرَّد مِن أَهْلِيَّة
40	جَرَّد مِن ثِقَة
41	حَكَم شَكْل خاطِئ
42	حِساب غَيْر دَقِيق
43	خال مِن مُنافَسَة
44	خَطا فِي تَرْتِيب
45	خَطَأ غَيْر مَقْصُود
46	خَطَأ فِي تَسْعِير
47	خَطَأ فِي تَصْنِيف
48	خَفَق فِي إِدارَة
49	خَلَل فِي تَسْعِير
50	خَلَل فِي تَواصُل

51	دَعْم مالِيّ طارِئ
52	دُون تَغْطِيَة تَأْمِين
53	دُون وَجْه حَقّ
54	رِبْح غَيْر مَشْرُوع
55	سَعَر شَكْل خاطِئ
56	سُوء فِي فَهْم
57	سُوء ٱِسْتِخْدام سُلْطَة
58	شَطْب مَبْلَغ مَدِينَة
59	شَكْل غَيْر أَخْلاقِيّ
60	شَكْل غَيْر ثابِت
61	شَكْل غَيْر دَقِيق
62	شَكْل غَيْر صادِق
63	شَكْل غَيْر صَحِيح
64	شَكْل غَيْر ضَرُورِيّ
65	شَكْل غَيْر طَبِيعِيّ
66	شَكْل غَيْر عادِل
67	شَكْل غَيْر فَعّال
68	شَكْل غَيْر قانُونِيّ
69	شَكْل غَيْر كافِي
70	شَكْل غَيْر كامِل
71	شَكْل غَيْر كُفُوء
72	شَكْل غَيْر لائِق
73	شَكْل غَيْر ماهِر
74	شَكْل غَيْر مَجْد
75	شَكْل غَيْر مَعْقُول
76	شَكْل غَيْر مَقْبُول
77	شَكْل غَيْر مَقْصُود
78	شَكْل غَيْر مَلام
79	شَكْل غَيْر مَنْطِقِيّ
80	شَكْل غَيْر مَوْثُوق
81	شَكْل غَيْر مُبالِي
82	شَكْل غَيْر مُبَرِّر
83	شَكْل غَيْر مُتَجانِس
84	شَكْل غَيْر مُتَساوِي
85	شَكْل غَيْر مُتَعَمَّد
86	شَكْل غَيْر مُتَكافِئ
87	شَكْل غَيْر مُتَناسِب
88	شَكْل غَيْر مُتَوازِن
89	شَكْل غَيْر مُتَوَقَّع
90	شَكْل غَيْر مُتَّسِق
91	شَكْل غَيْر مُخْلِص
92	شَكْل غَيْر مُسْتَمِرّ
93	شَكْل غَيْر مُفَضَّل
94	شَكْل غَيْر مُكْتَمَل
95	شَكْل غَيْر مُناسِب
96	شَكْل غَيْر مُنَظَّم
97	شَكْل غَيْر مُنْتَظِم
98	شَكْل غَيْر مُنْصِف
99	شَكْل غَيْر ناجِح
100	شَكْل غَيْر ٱِقْتِصادِيّ
101	شَكْل لا مُبالِي
102	شَكْل لَيِس مُنْتَظِم
103	شَكْل مَشْكُوك بِ

104	شَكْل مُثِير جَدَل
105	شَكْل مُثِير رِيبَة
106	شَكْل مُخالِف قانُون
107	صَرَّح شَكْل خاطِئ
108	صُورَة غَيْر دَقِيقَة
109	صُورَة غَيْر شَرِيف
110	صُورَة غَيْر شَرْعِيّ
111	صُورَة غَيْر طَبِيعِيّ
112	صُورَة غَيْر قانُونِيّ
113	صُورَة غَيْر مُبَرِّر
114	صُورَة غَيْر مُتَوَقَّع
115	صُورَة غَيْر مُفَضَّل
116	صُورَة غَيْر مُناسَبَة
117	صُورَة غَيْر مُنْتَظِم
118	صُورَة مُثِير جَدَل
119	طَرِيقَة غَيْر أَخْلاقِيّ
120	طَرِيقَة غَيْر دَقِيقَة
121	طَرِيقَة غَيْر شَرِيف
122	طَرِيقَة غَيْر طَبِيعِيّ
123	طَرِيقَة غَيْر عادِل
124	طَرِيقَة غَيْر قانُونِيّ
125	طَرِيقَة غَيْر مَقْبُول
126	طَرِيقَة غَيْر مُبَرِّر
127	طَرِيقَة غَيْر مُنْتَظِم
128	طَرِيقَة مُثِير جَدَل
129	عاجِز عَن دَفْع
130	عار مِن صِحَّة
131	عَجْز عَن سَداد
132	عَجْز فِي إِنْتاج
133	عَدَم إِبْلاغ كامِل
134	عَدَم جَدارَة نَصْح
135	عَدَم كِفايَة سُيُولَة
136	عَلَى فَتْرَة مُتَقَطِّع
137	عَن طَرِيق خَطَأ
138	عَن غَيْر قَصَد
139	عِبْء غَيْر مُجْدِي
140	غَيْر جَدِير تَقْدِير
141	غَيْر جَيِّد تِجارَة
142	غَيْر صالِح بَيْع
143	غَيْر صالِح اِسْتِخْدام
144	غَيْر صالِح اِسْتِعْمال
145	غَيْر قابِل إِلْغاء
146	غَيْر قابِل بَطَل
147	غَيْر قابِل بَيْع
148	غَيْر قابِل تَبْرِير
149	غَيْر قابِل تَحْصِيل
150	غَيْر قابِل تَداوُل
151	غَيْر قابِل تَسْلِيم
152	غَيْر قابِل تَسْوِيق
153	غَيْر قابِل تَطْبِيق
154	غَيْر قابِل تَعْوِيض
155	غَيْر قابِل تَنَبُّؤ
156	غَيْر قابِل تَنْفِيذ

157	غَيْر قابِل تِجارَة
158	غَيْر قابِل حُصُول
159	غَيْر قابِل نَقْض
160	غَيْر قابِل ٱِسْتِخْدام
161	غَيْر قابِل ٱِسْتِرْداد
162	غَيْر قابِل ٱِسْتِعادَة
163	غَيْر قَلِيل ٱِسْتِخْدام
164	غَيْر مَبْلَغ عَن
165	غَيْر مَجْدِي مالِيّ
166	غَيْر مَجْدِي ٱِقْتِصادِيّ
167	غَيْر مَدْعُوم مالِيّ
168	غَيْر مَرْحَب بِ
169	غَيْر مَرْغُوب بِ
170	غَيْر مَرْغُوب فِي
171	غَيْر مَسْمُوح بِ
172	غَيْر مُتَنَبِّئ بِ
173	غَيْر مُتَّفَق عِلْيَة
174	غَيْر مُحَقَّق طَمُوح
175	غَيْر مُحَقَّق هَدَف
176	غَيْر مُخَطَّط لِ
177	غَيْر مُسْتَغَلّ كامِل
178	غَيْر مُصَرَّح بِ
179	غَيْر مُغَطَّى تَأْمِين
180	غَيْر مُفْصِح عَن
181	غَيْر مُوافِق عَلَى
182	غَيْر مُوصَى بِ
183	فائِض فِي عَرْض
184	فَرَّط فِي إِنْتاج
185	فَرَّط فِي إِنْشاء
186	فَرَّط فِي تَثْمِين
187	فَرَّط فِي تَقْيِيم
188	فَشَل فِي أَداء
189	فِي غَيْر وَقْت
190	قَدَّر شَكْل خاطِئ
191	قَرَّر عَدَم أَهْلِيَّة
192	قَصْد إِلْحاق ضَرَر
193	قَصْر فِي تَقْرِير
194	قَصْر فِي ٱِسْتِخْدام
195	قَلَّل مِن تَقْدِير
196	قَلَّل مِن شَأن
197	كِذْب تَحْتَ قِسْم
198	لا أَساس لِ
199	لا أَمْكَن إِصْلاح
200	لا أَمْكَن إِلْغاء
201	لا أَمْكَن تَجَنُّب
202	لا أَمْكَن تَحْصِيل
203	لا أَمْكَن تَسْلِيم
204	لا أَمْكَن تَطْبِيق
205	لا أَمْكَن تَعْوِيض
206	لا أَمْكَن تَغْيِير
207	لا أَمْكَن تَنَبُّؤ
208	لا أَمْكَن حَمَل
209	لا أَمْكَن دَحْض

210	لا أمْكَن اِسْتِرْجاع
211	لا أمْكَن اِسْتِرْداد
212	لا أمْكَن اِسْتِعادَة
213	لا داعِي لِ
214	لا رَجْعَة فِي
215	لا قِيمَة لِ
216	لَم تَمّ تَحْصِيل
217	لَم تَمّ تَسْلِيم
218	لَم تَمّ كَشْف
219	لَم كَشَف عَن
220	لَيس مَجْدِي اِقْتِصادِيّ
221	ما قِبَل تَقاضِي
222	مَوْصُوف شَكْل خاطِئ
223	مُؤَرَّخ شَكْل خاطِئ
224	مُبالَغ فِي تَقْدِير
225	مُبالَغ فِي قِيمَة
226	مُبالَغَة فِي بِناء
227	مُبالَغَة فِي تَقْدِير
228	مُبالَغَة فِي قِيمَة
229	مُخالِف رُوح مُنافَسَة
230	مُسْتَحِقّ غَيْر مَدْفُوع
231	مُسْتَوْجِب مُلاحَقَة قَضائِيّ
232	مُصَنَّف شَكْل خَطَأ
233	مُغالِي فِي تَقْدِير
234	مُفْرِط فِي تَقْيِيم
235	نَحْو غَيْر أَخْلاقِيّ
236	نَحْو غَيْر ثابِت
237	نَحْو غَيْر دَقِيق
238	نَحْو غَيْر صَحِيح
239	نَحْو غَيْر طَبِيعِيّ
240	نَحْو غَيْر عادِل
241	نَحْو غَيْر فَعّال
242	نَحْو غَيْر قانُونِيّ
243	نَحْو غَيْر كافِي
244	نَحْو غَيْر مَجْدِي
245	نَحْو غَيْر مَقْبُول
246	نَحْو غَيْر مَلام
247	نَحْو غَيْر مُبالِي
248	نَحْو غَيْر مُبَرَّر
249	نَحْو غَيْر مُتَوَقَّع
250	نَحْو غَيْر مُتَّسِق
251	نَحْو غَيْر مُخْلِص
252	نَحْو غَيْر مُسْتَمِرّ
253	نَحْو غَيْر مُكْتَمَل
254	نَحْو غَيْر مُنْتَظِم
255	نَحْو غَيْر مُنْصِف
256	نَحْو غَيْر ناجِح
257	نَحْو لَيس مُنْتَظِم
258	نَحْو مُثِير جَدَل
259	نَحْو مُخالِف قانُون
260	اِنْعِدام جَداء مالِيّ

Table A3. (c-1) Uncertain English to Original Arabic Translation (*N =778*)

No.	English Word	Arabic Translation
1	abeyance	تعليق، توقف، إيقاف، تعطيل
2	almost	حوالي، قرابة
3	alteration	تبديل، تعديل
4	ambiguity	التباس، غموض، الالتباس، الإبهام
5	ambiguous	غامض، مبهم
6	anomalous	شاذة، غير عادي، غريب، منحرف، غير طبيعي
7	anomalously	بشكل غير طبيعي، بصورة غير طبيعية، بنحو غير طبيعي، بنحو شاذ، بشكل شاذ، بصورة شاذة، بطريقة شاذة
8	anomaly	شذوذ، انحراف، اختلال
9	anticipate	توقع، التنبؤ، يتنبأ، ينتظر، يتوقع، يستبق، يتحسب
10	anticipated	متوقع، مرتقب، يتوقع، منتظر، أستبق
11	anticipates	يتوقّع، يترقب، ينتظر، يستبق
12	anticipating	مُتَوَقّع، الترقب، التوقع، استباق، يتوقّع، يستبق
13	anticipation	الترقب، التوقع، تحسب، ترقب
14	apparent	ظاهر
15	apparently	يبدو
16	appear	يبدو، يظهر
17	appeared	يظهر، يبدو
18	appearing	يبدو، يظهر
19	appears	يبدو، يظهر
20	approximate	يقارب، يدنو، يقدر
21	approximated	تقريبي، مقارب
22	approximately	ما يقرب، تقريبًا، قرابة، حوالي
23	approximates	يقارب، يدنو، يتقارب، يقترب، يقدر
24	approximating	مقاربة، تقريب
25	approximation	مُقارَبَة، التقريب، تقريب
26	arbitrarily	تعسفي، بصورة عشوائية، بنحو عشوائي، بطريقة عشوائية، بشكل عشوائي
27	arbitrariness	اعتباطية، عشوائية، التعسف
28	arbitrary	اعتباطي، عشوائي، تعسفي
29	assume	يفترض، يظن، يعتقد، يتوقع
30	assumed	افترض، ظن، أعتقد، يفترض، مفترض
31	assumes	يفترض، يظن، يعتقد
32	assuming	افترض، يفترض، يظن، يعتقد، يتوقع
33	assumption	افترض، فرضية، توقع، اعتقاد
34	believe	اعتقاد، أعتقد، يظن، يفترض
35	believed	افترض، ظن، اعتقاد، اعتقد
36	believing	يفترض، ظن، يعتقد
37	cautious	متمهل، متحفظ، حذر، محترس
38	cautiously	بصورة متمهلة، بشكل متمهل، بطريقة متمهلة، بنحو متمهل، بشكل متحفظ، بطريقة متحفظة، بصورة متحفظة، بنحو متحفظ، بطريقة حذرة، بنحو حذر، بصورة حذرة، بشكل حذر
39	cautiousness	الحذر، التحفظ، الاحتراس
40	clarification	توضيح، إيضاح، استيضاح
41	conceivable	معقول، محتمل
42	conceivably	بشكل ممكن تصوره، بطريقة ممكن تصورها، بنحو ممكن تصورة، على نحو ممكن، على شكل ممكن، على طريقة ممكنة، من المعقول، من المحتمل
43	conditional	مقيد، مشروط
44	conditionally	بنحو مشروط، بشكل مشروط، بطريقة مشروطة، بصورة مشروطة، تحت شروط
45	confuses	يضلل، يربك، يشوش
46	confusing	مُحيّر، مربك، يربك، ملتبس، إرباك، مشوش، يشوش

No.	English Word	Arabic Translation
47	confusingly	بطريقة مربكة، بصورة مربكة، بشكل مربك، بنحو مربك، بشكل محير، بصورة محيرة، بطريقة محيرة، بنحو محير
48	confusion	ارتباك، إرباك، تداخل
49	contingency	طارئ، صدفة
50	contingent	محتمل، طارئ، مشروط
51	contingently	بشكل محتمل، بصورة محتملة، بنحو محتمل، بطريقة محتملة
52	could	ممكن أن، ربما
53	crossroad	منعطف، مفترق
54	depend	يتوقف، يعول
55	depended	يتوقف، عول
56	dependence	اعتمادية، الاتكال، التبعية
57	dependency	اعتمادية، الاتكال، التبعية
58	dependent	متكل
59	depending	يتوقف، اتكال، يتوقف
60	depends	معتمد عليه، يتوقف
61	destabilizing	يزعزع، إضطراب
62	deviate	تحيد، ينحرف، انحرف، يشذ
63	deviated	انحرف، منحرف، شاذ
64	deviating	الانحراف، ينحرف، شاذ
65	deviation	الانحراف، شذوذ
66	differ	يختلف، اختلاف
67	differed	اختلف، يتباين، تفاوت
68	differing	متفاوت، تباين، اختلاف
69	differs	يختلف
70	doubt	ريب، شك، تردد
71	doubted	شك، شكك، تردد، يشك
72	doubtful	مشكوك فيه، متردد، غير مؤكد، مبهم، محل شك، موضع شك
73	exposure	مكشوف، تعريض، تعرُّض
74	fluctuate	التقلب، تذبذب، يتذبذب، يتقلب، يتفاوت
75	fluctuated	تقلب، متقلب، تفاوت، متفاوت، تذبذب
76	fluctuates	يتذبذب، يتقلب، يتفاوت
77	fluctuating	تقلب، يتقلب، متقلب، تفاوت، متذبذب
78	fluctuation	تقلب، تذبذب
79	hidden	خفي، مخفي
80	hinge	يتوقف
81	imprecise	ضبابي، مبهم، غامض، فضفاض
82	imprecision	عدم الدقة، فقدان الدقة، عدم اليقين
83	improbability	عدم الاحتمالية
84	improbable	ضئيل الاحتمال، غير وارد، غير محتمل، بعيد الاحتمال، ليس محتمل
85	incompleteness	النقص
86	indefinite	غير محدد، أجل غير مسمى
87	indefinitely	لأجل غير مسمى، بلا نهاية، بشكل غير محدد، أجل غير مسمى
88	indefiniteness	عدم الوضوح
89	indeterminable	غير قابل للقياس، غير قابل للتحديد، لا يمكن تحديده
90	indeterminate	غير معين، غير قاطع، غير محدد
91	inexact	غير دقيق، غير صحيح
92	inexactness	عدم الصحة، عدم اليقين، عدم الدقة
93	instability	تقلب، انعدام استقرار، عدم الاستقرار، الاضطراب، عدم ثبات، تذبذب
94	intangible	غير ملموس، غير محسوس
95	likelihood	احتمال، مرجح
96	may	ربما
97	maybe	لعل، ربما

No.	English Word	Arabic Translation
98	might	ربما
99	nearly	حوالي، كاد، على وشك
100	nonassessable	غير قابل للتقييم، لا يمكن تقديره
101	occasionally	بعض الأحيان
102	ordinarily	معتاد، على نحو عادي
103	pending	عالقة، معلق
104	perhaps	لعل، ربما، على الأرجح
105	possibility	احتمال، إمكانية
106	possible	محتمل
107	possibly	يحتمل، ربما، احتمال
108	precaution	وقاية، حيطة
109	precautionary	احترازي، وقائي، تحوطي، احتراسي
110	predict	يتنبأ، يتوقع
111	predictability	قابلية التنبؤ، امكانيه التنبؤ، قادر على التنبأ، القدرة على التنبؤ
112	predicted	متوقع، التنبؤ، تنبأ
113	predicting	التنبؤ، يتنبأ، يتوقع
114	prediction	التنبؤ، التوقع
115	predictive	متوقع، قائم على التوقعات، يمكن التنبؤ بها
116	predictor	متوقع، متنبئ
117	predicts	يتنبأ، يتوقع
118	preliminarily	تمهيديًا
119	preliminary	مبدئي
120	presumably	محتمل، مرجحاً، على نحو محتمل، بشكل محتمل، بصورة محتملة
121	presume	يعتقد، يتوقع، يفترض، يظن
122	presumed	متوقع، افترض، افتراضي، مفترض، ظن
123	presumes	يفترض، يظن، يعتقد، يتوقع
124	presuming	ظن، توقع، اعتقاد، يعتقد، يفترض
125	presumption	الفرضية، ظن، الافتراض، الاعتقاد
126	probabilistic	محتمل، احتمالي، ترجيحي
127	probability	إحتمالية
128	probable	محتمل، متوقع، مرجح
129	probably	من المحتمل، من المرجح
130	random	عشوائي
131	randomize	عشوائي
132	randomly	بنحو عشوائي، بطريقة عشوائية، بشكل عشوائي، بصورة عشوائية
133	randomness	العشوائية
134	reassess	إعادة تقييم، إعادة تقدير، إعادة النظر
135	reassessed	إعادة تقييم، أعاد تقييم، إعادة تقدير، أعاد تقدير، أعاد النظر
136	reassesses	يعيد التقدير، يعيد تقييم، يعيد النظر
137	reassessing	إعادة تقييم، إعادة النظر، إعادة التقدير
138	reassessment	إعادة تقييم، إعادة تقدير، إعادة النظر
139	recalculate	،إعادة حساب، يعيد الحساب، إعادة التحليل، يعيد التحليل، إعادة التقدير، يعيد التقدير إعادة احتساب، يعيد احتساب
140	recalculated	تم إعادة الحساب، أعاد حسابة، أعاد تقديرة، أعاد تحليله، أعاد احتسابه
141	recalculates	يعيد التحليل، يعيد الحساب، يعيد التقدير، يعيد الاحتساب
142	recalculating	إعادة تحليل، إعادة تحديد، إعادة تقدير، إعادة احتساب، أعاد حسابة، أعاد تقديرة، أعاد تحليله، أعاد احتسابه
143	recalculation	إعادة الحساب، إعادة التحليل، إعادة التقدير، إعادة التحديد، إعادة احتساب
144	reconsider	يعيد تحليل، يعيد النظر، إعادة النظر، يعيد تقييم
145	reconsidered	أعيدت دراسته، أعاد النظر، أعاد التقييم، أعاد التحليل
146	reconsidering	إعادة النظر، إعادة التحليل، إعادة التقييم
147	reconsiders	يعيد التحليل، يعيد النظر، يعيد التقييم

No.	English Word	Arabic Translation
148	reexamination	إعادة الدراسة، إعادة النظر، إعادة الفحص، إعادة التحليل، إعادة التقييم
149	reexamine	يعيد فحص، يعيد تقييم، يعيد النظر
150	reexamining	إعادة النظر، إعادة التقييم، إعادة الفحص
151	reinterpret	يعيد النظر، يعيد تفسير
152	reinterpretation	إعادة التفسير، إعادة التأويل، إعادة النظر
153	reinterpreted	إعادة تأويل، أعاد تفسير، أعاد تأويل
154	reinterpreting	إعادة تفسير، إعادة تأويل
155	reinterprets	يعيد تفسير، يعيد التأويل
156	revise	يراجع، يعدل
157	revised	مُراجع
158	risk	مخاطر، خطورة، خطر، مخاطرة
159	risked	يخاطر، خطر
160	riskier	أكثر مخاطرة، أعلى خطورة، محفوف بالمخاطر، أكثر خطورة، أشد تعرضًا للمخاطر
161	riskiest	الأكثر مخاطرة، الأخطر، الأكثر خطورة، الأعلى خطورة
162	riskiness	الخطورة
163	risking	يجازف، يخاطر
164	risky	خطير، خطر
165	roughly	بشكل تقريبي
166	rumor	إشاعَة
167	seems	يبدو
168	seldom	نادراً
169	seldomly	بشكل نادر، على نحو نادر، بصورة نادرة
170	sometime	من حين لآخر
171	sometimes	من حين لآخر
172	somewhat	نوعًا ما، شيئا ما، إلى حد ما
173	somewhere	مكان ما، تقريبًا
174	speculate	يتكهن، يخمن، يضارب
175	speculated	يتكهن، يخمن، مضارب
176	speculates	يتكهن، يخمن، يضارب
177	speculating	التكهن، يتكهن، يخمن، مضاربة، يضارب
178	speculation	تخمين، التكهن، مضاربة
179	speculative	غير مؤكد، تخميني، تكهني
180	speculatively	بشكل تخميني، بشكل تكهني
181	sporadic	مشتت، عشوائي، متقطع، متفرق
182	sporadically	،بين الحين والآخر، بشكل غير منتظم، بشكل متفرق، بشكل مشتت، بشكل متقطع بنحو متقطع، بنحو مشتت، بنحو متفرق، بنحو غير منتظم
183	sudden	غير متوقع، مفاجئ
184	suddenly	بشكل مفاجئ، بطريقة مفاجئة، بدون سابق إنذار، مفاجئ، على نحو مفاجئ، بصورة مفاجئة
185	suggest	يقترح، يوحي
186	suggested	يقترح، مقترح
187	suggesting	يقترح، مما يوحي
188	suggests	يقترح
189	susceptibility	قابلية
190	tentative	مؤقت، متردد
191	tentatively	بشكل مبدئي، بشكل مؤقت
192	turbulence	تقلبات، اضطراب
193	uncertain	غامض، متردد، غير مؤكد
194	uncertainly	بشكل غير قاطع، بشكل غير مؤكد
195	uncertainty	الارتياب، التردد، الغموض
196	unclear	غامضا، غير واضح، مبهم
197	unconfirmed	غير مؤكد، غير معتمد

No.	English Word	Arabic Translation
198	undecided	غير مؤكد
199	undefined	غير موضح، غامض، غير معروف، غير محدد
200	undesignated	غير مخصص
201	undetectable	غير قابل للكشف
202	undeterminable	غير قابل للتعيين، غير قابل للتحديد
203	undetermined	غير معلوم، مبهم، غير مقرر، غير محدد
204	undocumented	بدون وثائق، غير موثق، غير مسجل
205	unexpected	غير متوقع، مفاجئ
206	unexpectedly	،بصورة غير متوقعة، بشكل غير متوقع، بنحو غير متوقع، بطريقة غير متوقعة بصورة مفاجئة، بنحو مفاجئ، بشكل مفاجئ، بطريقة مفاجئة
207	unfamiliar	غير مألوف، غير معتاد
208	unfamiliarity	نقص المعرفة، جهل، عدم الإلمام
209	unforecasted	غير متوقع، غير مخطط له، غير متنبأ به
210	unforseen	غير متوقع، غير مخطط له، مفاجئ
211	unguaranteed	غير مؤكد، غير مضمون، بدون ضمان، غير مكفول
212	unhedged	غير متحوط، غير محمي، دون تحوط
213	unidentifiable	مجهول، غير قابل للتعريف، غير قابل للتحديد، غير معروف
214	unidentified	مجهول، غير معروف
215	unknown	مجهول، غير معروف
216	unobservable	غير قابل للملاحظة، غير قابل للحفظ، لا يمكن ملاحظتها
217	unplanned	غير متوقع، غير مخطط، بدون تخطيط
218	unpredictable	غير متوقع، لا يمكن التنبؤ، غير قابل للتنبؤ، متقلب
219	unpredictably	بشكل مفاجئ، بشكل غير متوقع، بشكل غير محتمل، بصورة متقلبة، بشكل غير متوقع
220	unpredicted	غير متوقع، غير متنبئ به
221	unproved	غير مؤكد، غير مصادق عليه، غير مثبت، بدون دليل، بلا دليل
222	unproven	غير مبرهن، غير مؤكد، غير مثبت، بدون دليل، بلا دليل
223	unquantifiable	غير قابل للقياس، غير قابل للتحديد
224	unquantified	غير محدد الكمية، بدون قيمة محددة
225	unreconciled	غير مطابق، غير راضي، غير متصالح
226	unseasonable	في غير أوانه، غير جذاب
227	unseasonably	بشكل غير جذاب
228	unsettled	معلق
229	unspecific	غير محدد، غير واضح، فضفاض
230	unspecified	غير معين، غير موضح، غير معروفة، غير محدد
231	untested	غير مختبر، غير مجرب، دون تجريب
232	unusual	غير مألوف، نادر، غريب، غير عادي
233	unusually	بشكل نادر، نحو غير عادي، بشكل غير عادي، بصورة غير عادية، بشكل غير مألوف، بنحو غير مألوف، بصورة غير مألوفة، بطريقة غير مألوفة، بشكل غير معتاد، بنحو غير معتاد، بطريقة غير معتادة، بصورة غير معتادة
234	unwritten	شفوي، شفهي
235	vagary	غامض
236	vague	ضبابي، مبهم، غامض
237	vaguely	بشكل مبهم، بصورة مبهمة، بطريقة مبهمة، بطريقة غامضة، بصورة غامضة، بشكل غامض
238	vagueness	ضبابية، غموض
239	vaguer	أكثر ضبابية، أقل وضوحا، أكثر إبهاما، أكثر غموضا
240	vaguest	الأكثر ضبابية، اكثر غموضا، الأكثر غموضا، الأكثر إبهاما، الأقل وضوحا
241	variability	تقلب، تباين، تفاوت
242	variable	متقلب، متغير
243	variably	بشكل متقلب، بشكل متغير
244	variance	تباين، تغاير
245	variant	متباين، متفاوت، مغاير

No.	English Word	Arabic Translation
246	variation	تباين، انحراف، تفاوت
247	varied	متباين
248	varies	يتفاوت، يتراوح، يتقلب، يتباين
249	vary	تباين، يتغير، يتفاوت، يتباين، يختلف
250	varying	تباين، متقلب، يتباين، يتقلب
251	volatile	متقلب، غير مستقر
252	volatility	تقلب، تذبذب

Table A3. (c-2) Uncertain English to Lemmatized Arabic Translation (N =*778*)

No.	English Word	Arabic Translation
1	abeyance	تَعْلِيق، تَوَقُّف، إِيقاف، تَعْطِيل
2	almost	حِوال، قُرابَة
3	alteration	تَبْدِيل، تَعْدِيل
4	ambiguity	اِلْتِباس، غُمُوض، اِلْتِباس، إِبْهام
5	ambiguous	غامِض، مُبْهَم
6	anomalous	شاذّ، غَيْر عادِيّ، غَرِيب، مُنْحَرِف، غَيْر طَبِيعِيّ
7	anomalously	شَكْل غَيْر طَبِيعِيّ، صُورَة غَيْر طَبِيعِيّ، نَحْو غَيْر طَبِيعِيّ، نَحْو شاذّ، شَكْل شاذّ، صُورَة شاذّ، طَرِيقَة شاذّ
8	anomaly	شَذّ، اِنْحِراف، اِخْتِلال
9	anticipate	تَوَقَّع، تَنَبُّؤ، تَنَبَّأ، اِنْتَظَر، تَوَقَّع، اِسْتَبْقَى، تَحَسَّب
10	anticipated	مُتَوَقَّع، مُرْتَقَب، تَوَقَّع، مُنْتَظَر، اِسْتَبَق
11	anticipates	تَوَقَّع، تَرَقَّب، اِنْتَظَر، اِسْتَبْقَى
12	anticipating	مُتَوَقَّع، تَرَقَّب، تَوَقَّع، اِسْتِباق، تَوَقَّع، اِسْتَبْقَى
13	anticipation	تَرَقُّب، تَوَقَّع، تَحَسُّب، تَرَقَّب
14	apparent	ظاهِر
15	apparently	بَدا
16	appear	بَدا، أَظْهَر
17	appeared	أَظْهَر، بَدا
18	appearing	بَدا، أَظْهَر
19	appears	بَدا، أَظْهَر
20	approximate	قارَب، دَنا، قَدَّر
21	approximated	تَقْرِيبِيّ، مُقارِب
22	approximately	ما قَرُب، تَقْرِيب، قُرابَة، حِوال
23	approximates	قارَب، دَنا، تَقارَب، اِقْتَرَب، قَدَّر
24	approximating	مُقارَبَة، تَقْرِيب
25	approximation	مُقارَبَة، تَقْرِيب، تَقْرِيب
26	arbitrarily	تَعَسُّفِيّ، صُورَة عَشْوائِيّ، نَحْو عَشْوائِيّ، طَرِيقَة عَشْوائِيّ، شَكْل عَشْوائِيّ
27	arbitrariness	اِعْتِباطِيَّة، عَشْوائِيّ، تَعَسُّف
28	arbitrary	اِعْتِباطِيّ، عَشْوائِيّ، تَعَسُّفِيّ
29	assume	اِفْتَرَض، ظَنّ، اِعْتَقَد، تَوَقَّع
30	assumed	اِفْتَرَض، ظَنّ، اِعْتَقَد، اِفْتَرَض، مُفْتَرَض
31	assumes	اِفْتَرَض، ظَنّ، اِعْتَقَد
32	assuming	اِفْتَرَض، اِفْتَرَض، ظَنّ، اِعْتَقَد، تَوَقَّع
33	assumption	اِفْتَرَض، فَرْضِيَّة، تَوَقَّع، اِعْتِقاد
34	believe	اِعْتِقاد، اِعْتَقَد، ظَنّ، اِفْتَرَض
35	believed	اِفْتَرَض، ظَنّ، اِعْتِقاد، اِعْتَقَد
36	believing	اِفْتَرَض، ظَنّ، اِعْتَقَد
37	cautious	مُتَمَهِّل، مُتَحَفِّظ، حَذِّر، مُحْتَرِس
38	cautiously	صُورَة مُتَمَهِّل، شَكْل مُتَمَهِّل، طَرِيقَة مُتَمَهِّل، نَحْو مُتَمَهِّل، شَكْل مُتَحَفِّظ، طَرِيقَة مُتَحَفِّظ، صُورَة مُتَحَفِّظ، نَحْو مُتَحَفِّظ، طَرِيقَة حَذِّر، نَحْو حَذِّر، صُورَة حَذِّر، شَكْل حَذِّر
39	cautiousness	حِذْر، تَحَفُّظ، اِحْتِراس
40	clarification	تَوْضِيح، إِيضاح، اِسْتِيضاح
41	conceivable	مَعْقُول، مُحْتَمَل
42	conceivably	شَكْل مُمْكِن تَصَوَّر، طَرِيقَة مُمْكِن تَصَوَّر، نَحْو مُمْكِن تَصَوَّر، عَلَى نَحْو مُمْكِن، عَلَى شَكْل مُمْكِن، عَلَى طَرِيقَة مُمْكِن، مِن مَعْقُول، مِن مُحْتَمَل
43	conditional	مُقَيَّد، مَشْرُوط
44	conditionally	نَحْو مَشْرُوط، شَكْل مَشْرُوط، طَرِيقَة مَشْرُوط، صُورَة مَشْرُوط، تَحْتَ شَرْط
45	confuses	ضَلَّل، أَرْبَك، شَوَّش
46	confusing	مُحَيِّر، مُرْبِك، أَرْبَك، مُلْتَبِس، إِرْباك، مَشُوش، شَوَّش
47	confusingly	طَرِيقَة مُرْبِك، صُورَة مُرْبِك، شَكْل مُرْبِك، نَحْو مُرْبِك، شَكْل مُحَيِّر، صُورَة مُحَيِّر، طَرِيقَة مُحَيِّر، نَحْو مُحَيِّر

No.	English Word	Arabic Translation
48	confusion	اِرْتِباك، إرْباك، تَداخُل
49	contingency	طارِئ، صُدْفَة
50	contingent	مُحْتَمَل، طارِئ، مَشْرُوط
51	contingently	شَكْل مُحْتَمَل، صُورَة مُحْتَمَل، نَحْو مُحْتَمَل، طَرِيقَة مُحْتَمَل
52	could	مُمْكِن أنَّ، رُبَّما
53	crossroad	مُنْعَطَف، مُفْتَرَق
54	depend	تَوَقَّف، عَوَّل
55	depended	تَوَقَّف، عَوَّل
56	dependence	اعتماديه، اِتِّكال، تَبَعِيَّة
57	dependency	اعتماديه، اِتِّكال، تَبَعِيَّة
58	dependent	متكل
59	depending	تَوَقَّف، اِتِّكال، تَوَقَّف
60	depends	مُعْتَمَد عَلَى، تَوَقَّف
61	destabilizing	زَعْزَع، اِضْطِراب
62	deviate	حاد، اِنْحَرَف، اِنْحَرَف، شَذَّ
63	deviated	اِنْحَرَف، مُنْحَرِف، شاذّ
64	deviating	اِنْحِراف، اِنْحَرَف، شاذّ
65	deviation	اِنْحِراف، شَذَّ
66	differ	اِخْتَلَف، اِخْتِلاف
67	differed	اِخْتَلَف، تَبايَن، تَفاوُت
68	differing	مُتَفاوِت، تَبايُن، اِخْتِلاف
69	differs	اِخْتَلَف
70	doubt	رَيْب، شَكّ، تَرَدَّد
71	doubted	شَكّ، شَكَّك، تَرَدَّد، شَكّ
72	doubtful	مَشْكُوك فِي، مُتَرَدِّد، غَيْر مُؤَكِّد، مُبْهَم، مَحَلّ شَكّ، مَوْضِع شَكّ
73	exposure	مَكْشُوف، تَعْرِيض، تَعَرَّض
74	fluctuate	تَقَلَّب، تَذَبْذَب، تَذَبْذَب، تَقَلَّب، تَفاوَت
75	fluctuated	تَقَلَّب، مُتَقَلِّب، تَفاوُت، مُتَفاوِت، تَذَبْذَب
76	fluctuates	تَذَبْذَب، تَقَلَّب، تَفاوَت
77	fluctuating	تَقَلَّب، تَقَلَّب، مُتَقَلِّب، تَفاوُت، مُتَذَبْذِب
78	fluctuation	تَقَلَّب، تَذَبْذَب
79	hidden	خَفِيّ، مَخْفِيّ
80	hinge	تَوَقَّف
81	imprecise	ضَبابِيّ، مُبْهَم، غامِض، فَضْفاض
82	imprecision	عَدَم دِقَّة، فِقْدان دِقَّة، عَدَم يَقِين
83	improbability	عَدَم اِحْتِمالِيّ
84	improbable	ضَئِيل اِحْتِمال، غَيْر وارِد، غَيْر مُحْتَمَل، بَعِيد اِحْتِمال، لَيس مُحْتَمَل
85	incompleteness	نَقْص
86	indefinite	غَيْر مُحَدَّد، أجْل غَيْر مُسَمَّى
87	indefinitely	أجْل غَيْر مُسَمَّى، بِلا نِهايَة، شَكْل غَيْر مُحَدَّد، أجْل غَيْر مُسَمَّى
88	indefiniteness	عَدَم وُضُوح
89	indeterminable	غَيْر قابِل قِياس، غَيْر قابِل تَحْدِيد، لا أمْكَن تَحْدِيد
90	indeterminate	غَيْر مُعَيَّن، غَيْر قاطِع، غَيْر مُحَدَّد
91	inexact	غَيْر دَقِيق، غَيْر صَحِيح
92	inexactness	عَدَم صِحَّة، عَدَم يَقِين، عَدَم دِقَّة
93	instability	تَقَلَّب، اِنْعِدام اِسْتِقْرار، عَدَم اِسْتِقْرار، اِضْطِراب، عَدَم ثَبات، تَذَبْذَب
94	intangible	غَيْر مَلْمُوس، غَيْر مَحْسُوس
95	likelihood	اِحْتِمال، مُرَجِّح
96	may	رُبَّما
97	maybe	لَعَلَّ، رُبَّما
98	might	رُبَّما
99	nearly	حِوال، كاد، عَلَى وَشْك

No.	English Word	Arabic Translation
100	nonassessable	غَيْر قابِل تَقْيِيم، لا أَمْكَن تَقْدِير
101	occasionally	بعَضّ حِين
102	ordinarily	مُعْتاد، عَلَى نَحْو عادِيّ
103	pending	عالِق، مُعلّق
104	perhaps	لَعَلَّ، رُبَّما، عَلَى أرْجَح
105	possibility	اِحْتِمال، إمْكانِيَّة
106	possible	مُحْتَمَل
107	possibly	اِحْتَمَل، رُبَّما، اِحْتِمال
108	precaution	وِقايَة، حِيطَة
109	precautionary	اِحْتِراز، وِقائِيّ، تحوطي، اِحْتِراس
110	predict	تَنَبَّأ، تَوَقَّع
111	predictability	قابِلِيَّة تَنَبُّؤ، إمْكانِيَّة تَنَبُّؤ، قادِر عَلَى تنبا، قُدْرَة عَلَى تَنَبُّؤ
112	predicted	مُتَوَقَّع، تَنَبُّؤ، تَنَبَّأ
113	predicting	تَنَبُّؤ، تَنَبَّأ، تَوَقَّع
114	prediction	تَنَبُّؤ، تَوَقَّع
115	predictive	مُتَوَقَّع، قائِم عَلَى تَوَقَّع، أمْكَن تَنَبُّؤ بِ
116	predictor	مُتَوَقَّع، مُتَنَبِّئ
117	predicts	تَنَبَّأ، تَوَقَّع
118	preliminarily	تَمْهِيدِيّ
119	preliminary	مَبْدَئِيّ
120	presumably	مُحْتَمَل، مُرَجِّح، عَلَى نَحْو مُحْتَمَل، شَكْل مُحْتَمَل، صُورَة مُحْتَمَل
121	presume	اِعْتَقَد، تَوَقَّع، اِفْتَرَض، ظَنّ
122	presumed	مُتَوَقَّع، اِفْتَرَض، اِفْتِراضِيّ، مُفْتَرَض، ظَنّ
123	presumes	اِفْتَرَض، ظَنّ، اِعْتَقَد، تَوَقَّع
124	presuming	ظَنّ، تَوَقَّع، اِعْتِقاد، اِعْتَقَد، اِفْتَرَض
125	presumption	فَرْضِيَّة، ظَنّ، اِفْتِراض، اِعْتِقاد
126	probabilistic	مُحْتَمَل، اِحْتِمال، تَرْجِيحِيّ
127	probability	اِحْتِمال
128	probable	مُحْتَمَل، مُتَوَقَّع، مُرَجِّح
129	probably	مِن مُحْتَمَل، مِن مُرَجِّح
130	random	عَشْوائِيّ
131	randomize	عَشْوائِيّ
132	randomly	نَحْو عَشْوائِيّ، طَرِيقَة عَشْوائِيّ، شَكْل عَشْوائِيّ، صُورَة عَشْوائِيّ
133	randomness	عَشْوائِيّ
134	reassess	إعادَة تَقْيِيم، إعادَة تَقْدِير، إعادَة نَظَر
135	reassessed	إعادَة تَقْيِيم، أعاد تَقْيِيم، إعادَة تَقْدِير، أعاد تَقْدِير، أعاد نَظَر
136	reassesses	أعاد تَقْدِير، أعاد تَقْيِيم، أعاد نَظَر
137	reassessing	إعادَة تَقْيِيم، إعادَة نَظَر، إعادَة تَقْدِير
138	reassessment	إعادَة تَقْيِيم، إعادَة تَقْدِير، إعادَة نَظَر
139	recalculate	إعادَة حِساب، أعاد حِساب، إعادَة تَحْلِيل، أعاد تَحْلِيل، إعادَة تَقْدِير، أعاد تَقْدِير، إعادَة اِحْتِساب، أعاد اِحْتِساب
140	recalculated	تَمّ إعادَة حِساب، أعاد حِساب، أعاد تَقْدِير، أعاد تَحْلِيل، أعاد اِحْتِساب
141	recalculates	أعاد تَحْلِيل، أعاد حِساب، أعاد تَقْدِير، أعاد اِحْتِساب
142	recalculating	إعادَة تَحْلِيل، إعادَة تَحْدِيد، إعادَة تَقْدِير، إعادَة اِحْتِساب، أعاد حِساب، أعاد تَقْدِير، أعاد تَحْلِيل، أعاد اِحْتِساب
143	recalculation	إعادَة حِساب، إعادَة تَحْلِيل، إعادَة تَقْدِير، إعادَة تَحْدِيد، إعادَة اِحْتِساب
144	reconsider	أعاد تَحْلِيل، أعاد نَظَر، إعادَة نَظَر، أعاد تَقْيِيم
145	reconsidered	أعاد دِراسَة، أعاد نَظَر، أعاد تَقْيِيم، أعاد تَحْلِيل
146	reconsidering	إعادَة نَظَر، إعادَة تَحْلِيل، إعادَة تَقْيِيم
147	reconsiders	أعاد تَحْلِيل، أعاد نَظَر، أعاد تَقْيِيم
148	reexamination	إعادَة دِراسَة، إعادَة نَظَر، إعادَة فَحْص، إعادَة تَحْلِيل، إعادَة تَقْيِيم
149	reexamine	أعاد فَحْص، أعاد تَقْيِيم، أعاد نَظَر

No.	English Word	Arabic Translation
150	reexamining	إِعادَة نَظَر، إِعادَة تَقْيِيم، إِعادَة فَحْص
151	reinterpret	أَعاد نَظَر، أَعاد تَفْسِير
152	reinterpretation	إِعادَة تَفْسِير، إِعادَة تَأْوِيل، إِعادَة نَظَر
153	reinterpreted	إِعادَة تَأْوِيل، أَعاد تَفْسِير، أَعاد تَأْوِيل
154	reinterpreting	إِعادَة تَفْسِير، إِعادَة تَأْوِيل
155	reinterprets	أَعاد تَفْسِير، أَعاد تَأْوِيل
156	revise	راجَع، عَدَّل
157	revised	مُراجع
158	risk	مَخاطِر، خُطُورَة، خَطَر، مُخاطَرَة
159	risked	خاطَر، خَطَر
160	riskier	أَكْثَر مُخاطَرَة، أَعْلَى خُطُورَة، مَحْفُوف مَخاطِر، أَكْثَر خُطُورَة، أَشَدّ تَعَرَّض مَخاطِر
161	riskiest	أَكْثَر مُخاطَرَة، أَخْطَر، أَكْثَر خُطُورَة، أَعْلَى خُطُورَة
162	riskiness	خُطُورَة
163	risking	جازَف، خاطَر
164	risky	خَطِير، خَطَر
165	roughly	شَكْل تَقْرِيبِيّ
166	rumor	إِشاعَة
167	seems	بَدا
168	seldom	نادِر
169	seldomly	شَكْل نادِر، عَلَى نَحْو نادِر، صُورَة نادِر
170	sometime	مِن حِين آخَر
171	sometimes	مِن حِين آخَر
172	somewhat	نَوْع ما، شَيْء ما، إِلَى حَدّ ما
173	somewhere	مَكان ما، تَقْرِيب
174	speculate	تَكَهَّن، خَمَّن، ضارَب
175	speculated	تَكَهَّن، خَمَّن، مُضارِب
176	speculates	تَكَهَّن، خَمَّن، ضارَب
177	speculating	تَكَهُّن، تَكَهَّن، خَمَّن، مُضارِب، ضارَب
178	speculation	تَخْمِين، تَكَهُّن، مُضارِب
179	speculative	غَيْر مُؤَكِّد، تَخْمِين، تَكَهُّن
180	speculatively	شَكْل تَخْمِين، شَكْل تَكَهُّن
181	sporadic	مشتت، عَشْوائِيّ، مُتَقَطِّع، مُتَفَرِّق
182	sporadically	،بَيْن حِين آخَر، شَكْل غَيْر مُنْتَظِم، شَكْل مُتَفَرِّق، شَكْل مشتت، شَكْل مُتَقَطِّع، نَحْو مُتَقَطِّع نَحْو مشتت، نَحْو مُتَفَرِّق، نَحْو غَيْر مُنْتَظِم
183	sudden	غَيْر مُتَوَقَّع، مُفاجِئ
184	suddenly	شَكْل مُفاجِئ، طَرِيقَة مُفاجِئ، دُون سابِق إِنْذار، مُفاجِئ، عَلَى نَحْو مُفاجِئ، صُورَة مُفاجِئ
185	suggest	اِقْتَرَح، أَوْحَى
186	suggested	اِقْتَرَح، مُقْتَرَح
187	suggesting	اِقْتَرَح، مِن أَوْحَى
188	suggests	اِقْتَرَح
189	susceptibility	قابِلِيَّة
190	tentative	مُؤَقَّت، مُتَرَدِّد
191	tentatively	شَكْل مَبْدَئِيّ، شَكْل مُؤَقَّت
192	turbulence	تَقَلُّب، اِضْطِراب
193	uncertain	غامِض، مُتَرَدِّد، غَيْر مُؤَكِّد
194	uncertainly	شَكْل غَيْر قاطِع، شَكْل غَيْر مُؤَكِّد
195	uncertainty	اِرْتِياب، تَرَدُّد، غُمُوض
196	unclear	غامِض، غَيْر واضِح، مُبْهَم
197	unconfirmed	غَيْر مُؤَكِّد، غَيْر مُعْتَمَد
198	undecided	غَيْر مُؤَكِّد
199	undefined	غَيْر مُوَضِّح، غامِض، غَيْر مَعْرُوف، غَيْر مُحَدَّد
200	undesignated	غَيْر مُخَصَّص

No.	English Word	Arabic Translation
201	undetectable	غَيْر قابِل كَشْف
202	undeterminable	غَيْر قابِل تَعْيين، غَيْر قابِل تَحْدِيد
203	undetermined	غَيْر مَعْلُوم، مُبْهَم، غَيْر مُقَرّر، غَيْر مُحَدَّد
204	undocumented	دُون وَثِيقَة، غَيْر مَوْثِق، غَيْر مُسَجَّل
205	unexpected	غَيْر مُتَوَقَّع، مُفاجِئ
206	unexpectedly	صُورَة غَيْر مُتَوَقَّع، شَكْل غَيْر مُتَوَقَّع، نَحْو غَيْر مُتَوَقَّع، طَرِيقَة غَيْر مُتَوَقَّع، صُورَة مُفاجِئ، نَحْو مُفاجِئ، شَكْل مُفاجِئ، طَرِيقَة مُفاجِئ
207	unfamiliar	غَيْر مَأْلُوف، غَيْر مُعْتاد
208	unfamiliarity	نَقْص مَعْرِفَة، جَهْل، عَدَم إِلْمام
209	unforecasted	غَيْر مُتَوَقَّع، غَيْر مُخَطَّط لِ، غَيْر متنبا بِ
210	unforseen	غَيْر مُتَوَقَّع، غَيْر مُخَطَّط لِ، مُفاجِئ
211	unguaranteed	غَيْر مُؤَكَّد، غَيْر مَضْمُون، دُون ضَمان، غَيْر مَكْفُول
212	unhedged	غَيْر مُتَحَوِّط، غَيْر مَحْمِيّ، دُون حاط
213	unidentifiable	مَجْهُول، غَيْر قابِل تَعْرِيف، غَيْر قابِل تَحْدِيد، غَيْر مَعْرُوف
214	unidentified	مَجْهُول، غَيْر مَعْرُوف
215	unknown	مَجْهُول، غَيْر مَعْرُوف
216	unobservable	غَيْر قابِل مُلاحَظَة، غَيْر قابِل حِفْظ، لا أَمْكَن مُلاحَظَة
217	unplanned	غَيْر مُتَوَقَّع، غَيْر مُخَطَّط، دُون تَخْطِيط
218	unpredictable	غَيْر مُتَوَقَّع، لا أَمْكَن تَنَبُّؤ، غَيْر قابِل تَنَبُّؤ، مُتَقَلِّب
219	unpredictably	شَكْل مُفاجِئ، شَكْل غَيْر مُتَوَقَّع، شَكْل غَيْر مُحْتَمَل، صُورَة مُتَقَلِّب، شَكْل غَيْر مُتَوَقَّع
220	unpredicted	غَيْر مُتَوَقَّع، غَيْر مُتَنَبِّئ بِ
221	unproved	غَيْر مُؤَكَّد، غَيْر مصادق عَلَى، غَيْر مُثَبِّت، دُون دَلِيل، بِلا دَلِيل
222	unproven	غَيْر مبرهن، غَيْر مُؤَكَّد، غَيْر مُثَبِّت، دُون دَلِيل، بِلا دَلِيل
223	unquantifiable	غَيْر قابِل قِياس، غَيْر قابِل تَحْدِيد
224	unquantified	غَيْر مُحَدَّد كَمِّيَّة، دُون قِيمَة مُحَدَّد
225	unreconciled	غَيْر مطابق، غَيْر راضِي، غَيْر مُتَصالِح
226	unseasonable	فِي غَيْر أَوان، غَيْر جَذّاب
227	unseasonably	شَكْل غَيْر جَذّاب
228	unsettled	مُعَلَّق
229	unspecific	غَيْر مُحَدَّد، غَيْر واضِح، فَضْفاض
230	unspecified	غَيْر مُعَيَّن، غَيْر مُوَضِّح، غَيْر مَعْرُوف، غَيْر مُحَدَّد
231	untested	غَيْر مُخْتَبَر، غَيْر مُجَرَّب، دُون تَجْرِيب
232	unusual	غَيْر مَأْلُوف، نادِر، غَرِيب، غَيْر عادِيّ
233	unusually	شَكْل نادِر، نَحْو غَيْر عادِيّ، شَكْل غَيْر عادِيّ، صُورَة غَيْر عادِيّ، شَكْل غَيْر مَأْلُوف، نَحْو غَيْر مَأْلُوف، صُورَة غَيْر مَأْلُوف، طَرِيقَة غَيْر مَأْلُوف، شَكْل غَيْر مُعْتاد، نَحْو غَيْر مُعْتاد، طَرِيقَة غَيْر مُعْتاد، صُورَة غَيْر مُعْتاد
234	unwritten	شَفَوِيّ، شَفَهِيّ
235	vagary	غامِض
236	vague	ضَبابِيّ، مُبْهَم، غامِض
237	vaguely	شَكْل مُبْهَم، صُورَة مُبْهَم، طَرِيقَة مُبْهَم، طَرِيقَة غامِض، صُورَة غامِض، شَكْل غامِض
238	vagueness	ضَبابِيَّة، غُمُوض
239	vaguer	أَكْثَر ضَبابِيّ، أَقَلّ وُضُوح، أَكْثَر إِبْهام، أَكْثَر غُمُوض
240	vaguest	أَكْثَر ضَبابِيّ، أَكْثَر غُمُوض، أَكْثَر غُمُوض، أَكْثَر إِبْهام، أَقَلّ وُضُوح
241	variability	تَقَلُّب، تَبايُن، تَفاوُت
242	variable	مُتَقَلِّب، مُتَغَيِّر
243	variably	شَكْل مُتَقَلِّب، شَكْل مُتَغَيِّر
244	variance	تَبايُن، تَغايَر
245	variant	مُتَباين، مُتَفاوِت، مُغايِر
246	variation	تَبايُن، اِنْحِراف، تَفاوُت
247	varied	مُتَباين
248	varies	تَفاوَت، تَراوَح، تَقَلَّب، تَبايَن
249	vary	تَبايُن، تَغَيَّر، تَفاوَت، تَبايَن، اِخْتَلَف

No.	English Word	Arabic Translation
250	varying	تَبايُن، مُتَقَلِّب، تَبايَن، تَقَلَّب
251	volatile	مُتَقَلِّب، غَيْر مُسْتَقِرّ
252	volatility	تَقَلَّب، تَذَبْذَب

Table A3. (c-3.i) Uncertain Arabic One Word Dimensional (*N =182*)

No.	One Word Dimensional
1	أَخْطَر
2	أَرْبَك
3	أَظْهَر
4	أَوْحَى
5	إِبْهام
6	إِرْباك
7	إِشاعَة
8	إِمْكانِيَّة
9	إِيضاح
10	إِيقاف
11	اعتماديه
12	بَدا
13	تحوطي
14	تَبايَن
15	تَبايُن
16	تَبَعِيَّة
17	تَبْدِيل
18	تَحَسَّب
19	تَحَسُّب
20	تَحَفُّظ
21	تَخْمِين
22	تَداخُل
23	تَذَبْذَب
24	تَراوَح
25	تَرَدَّد
26	تَرَدُّد
27	تَرَقَّب
28	تَرَقُّب
29	تَرْجِيحِيّ
30	تَعَرَّض
31	تَعَسُّف
32	تَعَسُّفِيّ
33	تَعْدِيل
34	تَعْرِيض
35	تَعْطِيل
36	تَعْلِيق
37	تَغايَر
38	تَغَيَّر
39	تَفاوَت
40	تَفاوُت
41	تَقارَب
42	تَقَلَّب
43	تَقَلُّب
44	تَقْرِيب
45	تَقْرِيبِيّ
46	تَكَهَّن
47	تَكَهُّن
48	تَمْهِيدِيّ
49	تَنَبَّأ
50	تَنَبُّؤ

No.	One Word Dimensional
51	تَوَقَّع
52	تَوَقَّف
53	تَوَقَّع
54	تَوَقَّف
55	تَوْضِيح
56	جازَف
57	جَهْل
58	حاد
59	حَذَّر
60	حِذْر
61	حِوال
62	حِيطَة
63	خاطَر
64	خَطَر
65	خَطِير
66	خَفِيّ
67	خَمَّن
68	خُطُورَة
69	دَنا
70	راجَع
71	رَيْب
72	رُبَّما
73	زَعْزَع
74	شاذّ
75	شَذّ
76	شَفَهِيّ
77	شَفَوِيّ
78	شَكّ
79	شَكَّك
80	شَوَّش
81	صُدْفَة
82	ضارَب
83	ضَبابِيّ
84	ضَبابِيَّة
85	ضَلَّل
86	طارِئ
87	ظاهِر
88	ظَنّ
89	عالِق
90	عَدَّل
91	عَشْوائِيّ
92	عَوَّل
93	غامِض
94	غَرِيب
95	غُمُوض
96	فَرْضِيَّة
97	فَضْفاض
98	قابِلِيَّة
99	قارَب
100	قَدَّر
101	قُرابَة
102	كاد

No.	One Word Dimensional
103	لَعَلَّ
104	متكل
105	مشتت
106	مَبْدَئِيّ
107	مَجْهُول
108	مَخاطِر
109	مَخْفِيّ
110	مَشُوش
111	مَشْرُوط
112	مَعْقُول
113	مَكْشُوف
114	مُؤَقَّت
115	مُبْهَم
116	مُتَبايِن
117	مُتَحَفِّظ
118	مُتَذَبْذِب
119	مُتَرَدِّد
120	مُتَغَيِّر
121	مُتَفاوِت
122	مُتَفَرِّق
123	مُتَقَطِّع
124	مُتَقَلِّب
125	مُتَمَهِّل
126	مُتَنَبِّئ
127	مُتَوَقَّع
128	مُحَيَّر
129	مُحْتَرِس
130	مُحْتَمَل
131	مُخاطَرَة
132	مُراجع
133	مُرَجِّح
134	مُرْبِك
135	مُرْتَقَب
136	مُضارِب
137	مُعَلَّق
138	مُعْتاد
139	مُغايِر
140	مُفاجِئ
141	مُفْتَرَض
142	مُفْتَرَق
143	مُقارَبَة
144	مُقارِب
145	مُقَيَّد
146	مُقْتَرَح
147	مُلْتَبِس
148	مُنْتَظَر
149	مُنْحَرِف
150	مُنْعَطَف
151	نادِر
152	نَقْص
153	وِقائِيّ
154	وِقايَة

No.	One Word Dimensional
155	ٱِتِّكال
156	ٱِحْتَمَل
157	ٱِحْتِراز
158	ٱِحْتِراس
159	ٱِحْتِمال
160	ٱِخْتَلَف
161	ٱِخْتِلاف
162	ٱِخْتِلال
163	ٱِرْتِباك
164	ٱِرْتِياب
165	ٱِسْتَبَق
166	ٱِسْتَبْقَى
167	ٱِسْتِباق
168	ٱِسْتِيضاح
169	ٱِضْطِراب
170	ٱِعْتَقَد
171	ٱِعْتِباطِيّ
172	ٱِعْتِباطِيَّة
173	ٱِعْتِقاد
174	ٱِفْتَرَض
175	ٱِفْتِراض
176	ٱِفْتِراضِيّ
177	ٱِقْتَرَب
178	ٱِقْتَرَح
179	ٱِلْتِباس
180	ٱِنْتَظَر
181	ٱِنْحَرَف
182	ٱِنْحِراف

Table A3. (c-3.ii) Uncertain Arabic Two Words Dimensional (*N =170*)

No.	Two Words Dimensional
1	أَعاد تَأْوِيل
2	أَعاد تَحْلِيل
3	أَعاد تَفْسِير
4	أَعاد تَقْدِير
5	أَعاد تَقْيِيم
6	أَعاد حِساب
7	أَعاد دِراسَة
8	أَعاد فَحْص
9	أَعاد نَظَر
10	أَعاد اِحْتِساب
11	أَعْلَى خُطُورَة
12	أَقَلّ وُضُوح
13	أَكْثَر إِبْهام
14	أَكْثَر خُطُورَة
15	أَكْثَر ضَبابِيّ
16	أَكْثَر غُمُوض
17	أَكْثَر مُخاطَرَة
18	إِعادَة تَأْوِيل
19	إِعادَة تَحْدِيد
20	إِعادَة تَحْلِيل
21	إِعادَة تَفْسِير
22	إِعادَة تَقْدِير
23	إِعادَة تَقْيِيم
24	إِعادَة حِساب
25	إِعادَة دِراسَة
26	إِعادَة فَحْص
27	إِعادَة نَظَر
28	إِعادَة اِحْتِساب
29	إِمْكانِيَّة تَنَبُّؤ
30	بعَضّ حِين
31	بَعِيد اِحْتِمال
32	بِلا دَلِيل
33	بِلا نِهايَة
34	تَحْتَ شَرْط
35	دُون تَجْرِيب
36	دُون تَخْطِيط
37	دُون حاط
38	دُون دَلِيل
39	دُون ضَمان
40	دُون وَثِيقَة
41	شَكْل تَخْمِين
42	شَكْل تَقْرِيبِيّ
43	شَكْل تَكَهُّن
44	شَكْل حَذِّر
45	شَكْل شاذّ
46	شَكْل عَشْوائِيّ
47	شَكْل غامِض
48	شَكْل مشتت
49	شَكْل مَبْدَئِيّ
50	شَكْل مَشْرُوط

No.	Two Words Dimensional
51	شَكْل مُؤَقّت
52	شَكْل مُبْهَم
53	شَكْل مُتَحَفِّظ
54	شَكْل مُتَغَيِّر
55	شَكْل مُتَفَرّق
56	شَكْل مُتَقَطِّع
57	شَكْل مُتَقَلِّب
58	شَكْل مُتَمَهِّل
59	شَكْل مُحَيِّر
60	شَكْل مُحْتَمَل
61	شَكْل مُرْبِك
62	شَكْل مُفاجِئ
63	شَكْل نادِر
64	شَيْء ما
65	صُورَة حَذِّر
66	صُورَة شاذّ
67	صُورَة عَشْوائِيّ
68	صُورَة غامِض
69	صُورَة مَشْرُوط
70	صُورَة مُبْهَم
71	صُورَة مُتَحَفِّظ
72	صُورَة مُتَقَلِّب
73	صُورَة مُتَمَهِّل
74	صُورَة مُحَيِّر
75	صُورَة مُحْتَمَل
76	صُورَة مُرْبِك
77	صُورَة مُفاجِئ
78	صُورَة نادِر
79	ضَئِيل اِحْتِمال
80	طَرِيقَة حَذِّر
81	طَرِيقَة شاذّ
82	طَرِيقَة عَشْوائِيّ
83	طَرِيقَة غامِض
84	طَرِيقَة مَشْرُوط
85	طَرِيقَة مُبْهَم
86	طَرِيقَة مُتَحَفِّظ
87	طَرِيقَة مُتَمَهِّل
88	طَرِيقَة مُحَيِّر
89	طَرِيقَة مُحْتَمَل
90	طَرِيقَة مُرْبِك
91	طَرِيقَة مُفاجِئ
92	عَدَم إِلْمام
93	عَدَم ثَبات
94	عَدَم دِقّة
95	عَدَم صِحَّة
96	عَدَم وُضُوح
97	عَدَم يَقِين
98	عَدَم اِحْتِمالِيّ
99	عَدَم اِسْتِقْرار
100	عَلَى أَرْجَح
101	عَلَى وَشْك
102	غَيْر جَذّاب

No.	Two Words Dimensional
103	غَيْر دَقِيق
104	غَيْر راضِي
105	غَيْر صَحِيح
106	غَيْر طَبِيعِيّ
107	غَيْر عادِيّ
108	غَيْر قاطِع
109	غَيْر مبرهن
110	غَيْر مطابق
111	غَيْر مَأْلُوف
112	غَيْر مَحْسُوس
113	غَيْر مَحْمِيّ
114	غَيْر مَضْمُون
115	غَيْر مَعْرُوف
116	غَيْر مَعْلُوم
117	غَيْر مَكْفُول
118	غَيْر مَلْمُوس
119	غَيْر مَوْثِق
120	غَيْر مُؤَكِّد
121	غَيْر مُتَحَوِّط
122	غَيْر مُتَصالِح
123	غَيْر مُتَوَقَّع
124	غَيْر مُثَبِّت
125	غَيْر مُجَرَّب
126	غَيْر مُحَدَّد
127	غَيْر مُحْتَمَل
128	غَيْر مُخَصَّص
129	غَيْر مُخَطّط
130	غَيْر مُخْتَبَر
131	غَيْر مُسَجَّل
132	غَيْر مُسْتَقِرّ
133	غَيْر مُعَيَّن
134	غَيْر مُعْتاد
135	غَيْر مُعْتَمَد
136	غَيْر مُقَرِّر
137	غَيْر مُوَضِّح
138	غَيْر وارِد
139	غَيْر واضِح
140	فِقْدان دِقَّة
141	قابِلِيَّة تَنَبُّؤ
142	لَيِس مُحْتَمَل
143	ما قَرُب
144	مَحَلّ شَكّ
145	مَحْفُوف مَخاطِر
146	مَشْكُوك فِي
147	مَكان ما
148	مَوْضِع شَكّ
149	مُعْتَمَد عَلَى
150	مُمْكِن أَنَّ
151	مِن أَوْحَى
152	مِن مَعْقُول
153	مِن مُحْتَمَل
154	مِن مُرَجِّح

No.	Two Words Dimensional
155	نَحْو حَذِّر
156	نَحْو شاذّ
157	نَحْو عَشْوائِيّ
158	نَحْو مشتت
159	نَحْو مَشْرُوط
160	نَحْو مُتَحَفِّظ
161	نَحْو مُتَفَرِّق
162	نَحْو مُتَقَطِّع
163	نَحْو مُتَمَهِّل
164	نَحْو مُحَيَّر
165	نَحْو مُحْتَمَل
166	نَحْو مُرْبِك
167	نَحْو مُفاجِئ
168	نَقْص مَعْرِفَة
169	نَوْع ما
170	اِنْعِدام اِسْتِقْرار

Table A3. (c-3.iii) Uncertain Arabic Three Words Dimensional (*N* =*66*)

No.	Three Words Dimensional
1	أَجْل غَيْر مُسَمَّى
2	أَشَدّ تَعَرَّض مَخاطِر
3	أَمْكَن تَنَبُّؤ بِ
4	إِلَى حَدّ ما
5	بَيْن حِين آخَر
6	تَمّ إِعادَة حِساب
7	دُون سابِق إِنْذار
8	دُون قِيمَة مُحَدَّد
9	شَكْل غَيْر جَذّاب
10	شَكْل غَيْر طَبِيعِيّ
11	شَكْل غَيْر عادِيّ
12	شَكْل غَيْر قاطِع
13	شَكْل غَيْر مَأْلُوف
14	شَكْل غَيْر مُؤَكَّد
15	شَكْل غَيْر مُتَوَقَّع
16	شَكْل غَيْر مُحَدَّد
17	شَكْل غَيْر مُحْتَمَل
18	شَكْل غَيْر مُعْتاد
19	شَكْل غَيْر مُنْتَظِم
20	شَكْل مُمْكِن تَصَوَّر
21	صُورَة غَيْر طَبِيعِيّ
22	صُورَة غَيْر عادِيّ
23	صُورَة غَيْر مَأْلُوف
24	صُورَة غَيْر مُتَوَقَّع
25	صُورَة غَيْر مُعْتاد
26	طَرِيقَة غَيْر مَأْلُوف
27	طَرِيقَة غَيْر مُتَوَقَّع
28	طَرِيقَة غَيْر مُعْتاد
29	طَرِيقَة مُمْكِن تَصَوَّر
30	عَلَى شَكْل مُمْكِن
31	عَلَى طَرِيقَة مُمْكِن
32	عَلَى نَحْو عادِيّ
33	عَلَى نَحْو مُحْتَمَل
34	عَلَى نَحْو مُفاجِئ
35	عَلَى نَحْو مُمْكِن
36	عَلَى نَحْو نادِر
37	غَيْر قابِل تَحْدِيد
38	غَيْر قابِل تَعْرِيف
39	غَيْر قابِل تَعْيِين
40	غَيْر قابِل تَقْيِيم
41	غَيْر قابِل تَنَبُّؤ
42	غَيْر قابِل حِفْظ
43	غَيْر قابِل قِياس
44	غَيْر قابِل كَشْف
45	غَيْر قابِل مُلاحَظَة
46	غَيْر متنبا بِ
47	غَيْر مصادق عَلَى
48	غَيْر مُتَنَبِّئ بِ
49	غَيْر مُحَدَّد كَمِّيَّة
50	غَيْر مُخَطَّط لِ

No.	Three Words Dimensional
51	فِي غَيْر أَوان
52	قائِم عَلَى تَوَقّع
53	قادِر عَلَى تنبا
54	قُدْرَة عَلَى تَنَبُّؤ
55	لا أَمْكَن تَحْدِيد
56	لا أَمْكَن تَقْدِير
57	لا أَمْكَن تَنَبُّؤ
58	لا أَمْكَن مُلاحَظَة
59	مِن حِين آخَر
60	نَحْو غَيْر طَبِيعِيّ
61	نَحْو غَيْر عادِيّ
62	نَحْو غَيْر مَأْلُوف
63	نَحْو غَيْر مُتَوَقّع
64	نَحْو غَيْر مُعْتاد
65	نَحْو غَيْر مُنْتَظِم
66	نَحْو مُمْكِن تَصَوَّر

Chapter 4 - Appendix B

Appendix B.1 - Summary Statistics of the Arabic and English Textual Data Construction

The appendix presents summary statistics for all textual financial datasets prior to sentiment classification. It includes the original Arabic and English extractions from annual reports and CEO letters, alongside their corresponding machine-translated counterparts. Each corpus is described in two phases: the initial unprocessed extraction and the preprocessing stage, which involves normalization and tokenization but excludes stop-word removal. These phases are then further processed for the stop-word removal step, which aligns with the corpus summary statistics reported in Chapter 4.

Table B.1 (a-1) Summary Statistics of the Annual Reports and CEO Letters (Initial Extracted Texts Stage)

	Document	Total Token	Tokens per document				
			Mean	Median	SD	Min	Max
Panel A: Annual reports							
Arabic	728	8,450,915	11,608	9,003	8,827	658	63,276
English	728	9,849,156	13,529	11,192	9,227	865	65,811
Panel B: CEO letters							
Arabic	274	225,288	822	642	610	135	3,953
English	274	250,101	916	771	626	101	4,145

This table presents summary statistics of the annual reports and CEO letters in Arabic and their corresponding versions in English. The summary reports the tokenized corpora prior to pre-processing, cleaning, and stopword removal. The textual datasets presented in this summary denote the initial stage of subsequent pre-processing, translation, and textual analysis procedures.

Table B.1 (a-2) Summary Statistics of the Annual Reports and CEO Letters (Pre-processing Stage)

	Document	Total words	Words per document				
			Mean	Median	SD	Min	Max
Panel A: Annual reports							
Arabic	728	7,435,792	10,214	7,890	7,784	553	55,298
English	728	7,155,512	9,829	8,095	6,698	610	46,741
Panel B: CEO letters							
Arabic	274	200,294	731	581	533	124	3,458
English	274	183,306	669	567	456	75	2,975

This table presents summary statistics of the annual reports and CEO letters in Arabic and their corresponding versions in English. The summary reports the corpora after establishing the word definition across both languages. In Arabic, a word is defined as a sequence of at least two characters, while in English, a word is defined as a sequence of at least three characters. The textual datasets presented in this summary reflect the second stage of the pre-processing step, in which the stop words are retained.

Table B.1 (b-1) Summary Statistics of the Machine-Translated Annual Reports and CEO Letters (Initial translated Texts Stage)

	Document	Total Token	Tokens per document				
			Mean	Median	SD	Min	Max
Panel A: Annual reports							
Translated Arabic	728	8,153,612	11,200	8,826	8,250	711	60,058
Translated English	728	10,770,671	14,794	11,838	10,582	874	75,228
Panel B: CEO letters							
Translated Arabic	274	215,263	785	633	583	76	3,984
Translated English	274	283,503	1,034	851	703	178	4,120

This table presents summary statistics of the initial machine-translation versions of the annual reports and CEO letters in Arabic and their corresponding versions in English. Translated Arabic reports represent documents translated from English into Arabic, while Translated English reports reflect the translation from Arabic into English. The translations were conducted using the Google Cloud Translation API service. The summary reports the tokenized corpora prior to pre-processing, cleaning, and stopword removal. The textual datasets presented in this summary denote the initial stage of subsequent pre-processing and sentiment analysis conducted on the translated text.

Table B.1 (b-2) Summary Statistics of the Machine-Translated Annual Reports and CEO Letters (Pre-processing Stage)

	Document	Total Token	Tokens per document				
			Mean	Median	SD	Min	Max
Panel A: Annual reports							
Translated Arabic	728	7,102,368	9,756	7,627	7,241	598	52,006
Translated English	728	7,743,008	10,636	8,373	7,689	579	53,388
Panel B: CEO letters							
Translated Arabic	274	190,109	693	562	511	68	3,556
Translated English	274	205,670	750	623	513	134	2,956

This table presents summary statistics of the initial machine-translation versions of the annual reports and CEO letters in Arabic and their corresponding versions in English. Translated Arabic reports represent documents translated from English into Arabic, while Translated English reports reflect the translation from Arabic into English. The translations were conducted using the Google Cloud Translation API service. The summary reports the corpora after establishing the word definition across both languages. In Arabic, a word is defined as a sequence of at least two characters, while in English, a word is defined as a sequence of at least three characters. The textual datasets presented in this summary reflect the second stage of the pre-processing step, in which the stop words are retained.

Appendix B.2 - Arabic Lemmatization with CAMeL Tools: MLE vs BERT-based disambiguator

The appendix documents the comparative lemmatization performance of the two available morphological disambiguation models in the CAMeL library before selecting the model to process the Arabic financial text. It provides a statistical summary of the proportion of each sentiment category, correlation analysis, and sentiment classification across the two models:

Table B.2 (a-1) Maximum Likelihood Estimation (MLE) Vs. BERT-based disambiguator Sentiment Analysis

	Maximum Likelihood Estimation (MLE)					BERT-based disambiguator					Pairwise Corr.	Spearman Corr.
	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)		
Panel A: Annual reports *N= 728*												
NEG	2.34	2.21	0.74	0.50	5.47	2.23	2.09	0.72	0.50	5.35	0.989***	0.986***
POS	4.20	3.82	1.70	0.89	10.52	4.13	3.78	1.71	0.89	10.71	0.999***	0.998***
UNC	1.80	1.71	0.66	0.08	4.03	1.73	1.64	0.64	0.08	4.00	0.989***	0.992***
Panel B: CEO letters *N= 274*												
NEG	1.79	1.55	1.31	0.00	7.05	1.80	1.61	1.29	0.00	7.50	0.985***	0.979***
POS	10.46	10.76	2.88	2.92	20.76	10.47	10.64	2.83	2.88	20.94	0.991***	0.990***
UNC	0.69	0.61	0.54	0.00	2.76	0.64	0.58	0.51	0.00	2.43	0.916***	0.939***

The table presents summary statistics of sentiment words in Arabic annual reports and CEO letters, based on the Arabic financial sentiment dictionary (ArFinSD), across Arabic text processed using the Maximum Likelihood Estimation (MLE) and BERT-based disambiguator. Additionally, this table displays simple pairwise correlations and Spearman rank correlations. These correlations relate to negative, positive, and uncertain word lists from ArFinSD utilizing two different lemmatization models. ***, **, and * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B.2 (a-2) Most Frequent Sentiment Words Occurring in Arabic Annual Reports

Rank	**Maximum Likelihood Estimation (MLE)**				**BERT-based disambiguator**			
	Word	Total	%	Cum%	Word	Total	%	Cum%
Panel A: Most common positive words								
1	تَحْقِيق	16,828	5.86	5.86	تَحْقِيق	16,827	5.88	5.88
2	تَطْوِير	15,819	5.51	11.36	تَطْوِير	15,741	5.50	11.37
3	نُمُوّ	11,890	4.14	15.50	نُمُوّ	11,888	4.15	15.52
4	تَعْزِيز	11,499	4.00	19.51	تَعْزِيز	11,499	4.01	19.54
5	دَعْم	9,777	3.40	22.91	دَعْم	9,791	3.42	22.96
6	قُدْرَة	9,434	3.28	26.19	تَحْسِين	8,866	3.10	26.05
7	تَحْسِين	8,875	3.09	29.28	قُدْرَة	8,798	3.07	29.12
8	ضَمان	8,431	2.93	32.22	ضَمان	8,430	2.94	32.07
9	كَفاءَة	7,015	2.44	34.66	أَفْضَل	7,078	2.47	34.54
10	أَعْلَى	6,627	2.31	36.97	كَفاءَة	7,012	2.45	36.99
All		282,927				281,502		
Panel B: Most common negative words								
1	خَسارَة	7,431	5.86	5.86	خَسارَة	7,431	6.10	6.10
2	اِنْخِفاض	5,079	4.01	9.87	اِنْخِفاض	5,079	4.17	10.26
3	تَحَدِّي	3,407	2.69	12.55	تَحَدِّي	3,404	2.79	13.06
4	تَعْوِيض	2,904	2.29	14.84	تَعْوِيض	2,904	2.38	15.44
5	تَقْلِيل	2,744	2.16	17.01	تَقْلِيل	2,744	2.25	17.69
6	خَضَع	2,037	1.61	18.62	خَضَع	2,037	1.67	19.36
7	سَلْبِيّ	1,983	1.56	20.18	سَلْبِيّ	1,977	1.62	20.98
8	تَخْفِيض	1,686	1.33	21.51	تَخْفِيض	1,686	1.38	22.37
9	عارَض	1,655	1.31	22.81	تَعارُض	1,626	1.33	23.70
10	مُواجَهَة	1,545	1.22	24.03	ضُعْف	1,554	1.27	24.98
All		139,645				134,755		
Panel C: Most common uncertain words								
1	مَخاطِر	44,938	51.97	51.97	مَخاطِر	45,856	54.74	54.74
2	مُتَوَقَّع	4,586	5.30	57.28	مُتَوَقَّع	4,585	5.47	60.21
3	مُقْتَرَح	2,995	3.46	60.74	مُقْتَرَح	2,995	3.57	63.78
4	تَعَرَّض	2,684	3.10	63.84	تَوَقُّع	2,857	3.41	67.19
5	مُحْتَمَل	2,677	3.10	66.94	مُحْتَمَل	2,677	3.20	70.39
6	تَوَقُّع	2,662	3.08	70.02	مُتَغَيِّر	1,749	2.09	72.48
7	قَدَّر	2,353	2.72	72.74	تَعَرَّض	1,727	2.06	74.54
8	مُتَغَيِّر	1,749	2.02	74.76	مَعْقُول	1,521	1.82	76.35
9	مَعْقُول	1,579	1.83	76.59	إِيضاح	1,405	1.68	78.03
10	إِيضاح	1,406	1.63	78.21	إِمْكانِيَّة	1,403	1.67	79.70
All		104,580				101,725		

This comparison table demonstrates the similarity of sentiment classification across negative, positive, and uncertain categories, as identified in the annual reports. The analysis is conducted on Arabic text processed by employing the Maximum Likelihood Estimation (MLE) and BERT-based disambiguator. The occurrences of Arabic words were computed using the Arabic Financial Sentiment Dictionary (ArFinSD).

Table B.2 (a-3) Most Frequent Sentiment Words Occurring in Arabic CEO Letters

Rank	**Maximum Likelihood Estimation (MLE)**				**BERT-based disambiguator**			
	Word	Total	%	Cum%	Word	Total	%	Cum%
Panel A: Most common positive words								
1	نُمُوّ	1,132	6.67	6.67	نُمُوّ	1,132	6.63	6.63
2	تَحْقِيق	1,094	6.44	13.11	تَحْقِيق	1,094	6.41	13.03
3	تَعْزِيز	761	4.48	17.59	تَعْزِيز	761	4.46	17.49
4	تَطْوِير	725	4.27	21.86	تَطْوِير	722	4.23	21.72
5	دَعْم	613	3.61	25.47	دَعْم	617	3.61	25.33
6	نَجاح	493	2.90	28.38	حَقَّق	507	2.97	28.30
7	حَقَّق	485	2.86	31.23	نَجاح	493	2.89	31.18
8	تَحْسِين	398	2.34	33.58	أَفْضَل	413	2.42	33.60
9	إِنْجاز	384	2.26	35.84	تَحْسِين	396	2.32	35.92
10	فُرْصَة	384	2.26	38.10	إِنْجاز	384	2.25	38.17
All		16,882				16,933		
Panel B: Most common negative words								
1	تَحَدِّي	343	13.10	13.10	تَحَدِّي	345	13.50	13.50
2	خَسارَة	103	3.93	17.04	خَسارَة	103	4.03	17.53
3	اِنْخِفاض	95	3.63	20.66	اِنْخِفاض	95	3.72	21.24
4	خَفْض	75	2.86	23.53	خَفْض	75	2.93	24.18
5	مُواجَهَة	74	2.83	26.36	مُواجَهَة	74	2.90	27.07
6	تَقْلِيل	63	2.41	28.76	تَقْلِيل	63	2.46	29.54
7	صَعْب	55	2.10	30.86	صَعْب	55	2.15	31.69
8	تَداعِي	51	1.95	32.81	تَداعِي	51	2.00	33.69
9	بالِغ	49	1.87	34.68	بالِغ	49	1.92	35.60
10	أَزْمَة	46	1.76	36.44	أَزْمَة	46	1.80	37.40
All		2,746				2,678		
Panel C: Most common uncertain words								
1	مَخاطِر	110	11.92	11.92	مَخاطِر	111	12.64	12.64
2	قَدَّر	77	8.34	20.26	تَوَقُّع	80	9.11	21.75
3	تَوَقُّع	74	8.02	28.28	مُتَوَقَّع	71	8.09	29.84
4	مُتَوَقَّع	71	7.69	35.97	مُتَغَيِّر	66	7.52	37.36
5	تَوَقَّع	66	7.15	43.12	أَظْهَر	64	7.29	44.65
6	مُتَغَيِّر	66	7.15	50.27	إِمْكانِيَّة	63	7.18	51.82
7	أَظْهَر	63	6.83	57.10	تَوَقَّع	59	6.72	58.54
8	إِمْكانِيَّة	63	6.83	63.92	حِوال	39	4.44	62.98
9	حِوال	36	3.90	67.82	قَدَّر	25	2.85	65.83
10	مُحْتَمَل	23	2.49	70.31	مُحْتَمَل	23	2.62	68.45
All		1,103				1,057		

This comparison table demonstrates the similarity of sentiment classification across negative, positive, and uncertain categories, as identified in CEO letters. The analysis is conducted on Arabic text processed by employing the Maximum Likelihood Estimation (MLE) and BERT-based disambiguator. The occurrences of Arabic words were computed using the Arabic Financial Sentiment Dictionary (ArFinSD).

Appendix B.3 - Stemming as an Alternative Approach for Word-Level Representation

Stemming and lemmatizing are normalization techniques that aim to reduce the word to its basic form. However, these two techniques differ, with stemming being aggressive in reducing the word to its root. Given the semantic and morphological complexity of the Arabic language, the research conducted further investigation into the best word representation for Arabic-English financial text through a dictionary-based sentiment analysis. These analyses collectively demonstrate that Arabic lemmatization is superior for accurately representing the word's surface level compared to stemming. In English, the research further confirms the findings of previous studies, such as Loughran and McDonald (2011) and Bannier et al. (2019), who demonstrated that inflected word forms are more accurate than stemming in dictionary-based sentiment analysis settings. However, in comparison between English and Arabic, stemming in English achieves significantly higher word representation accuracy than in Arabic financial text. Stemming in Arabic is known for aggressively reducing the word to its roots, which creates extreme ambiguity as the root can generate numerous derivational and inflected forms, which may differ in meaning and grammatical function. As a result, this can negatively impact the accuracy of sentiment classification. For example, the root كتب can be the stem of semantically distinct words such as كاتب (writer), مكتبه (library), كتاب (book), كتب (to write), and مكتوب (written). The following are word sentiment frequencies and summary statistics on different sentiment classification settings involving stemming as an alternative approach for Arabic and English:

Table B.3 (a-1) Most Frequent Sentiment Words Occurring in English Annual Reports

Rank	**Stemmed word forms**				**Inflected word forms**			
	Word	Total	%	Cum%	Word	Total	%	Cum%
Panel A: Most common positive words								
1	achiev	14,409	8.01	8.01	achieve	5,493	4.68	4.68
2	profit	14,083	7.83	15.84	best	5,004	4.26	8.93
3	posit	10,595	5.89	21.73	efficiency	4,216	3.59	12.52
4	inform	10,298	5.73	27.46	opportunities	3,920	3.34	15.86
5	improv	8,732	4.85	32.31	enhance	3,403	2.90	18.76
6	enhanc	7,198	4.00	36.31	strong	3,274	2.79	21.54
7	success	6,155	3.42	39.74	achieving	3,122	2.66	24.20
8	effici	6,132	3.41	43.15	improve	3,108	2.65	26.85
9	integr	5,781	3.21	46.36	leading	3,008	2.56	29.41
10	benefit	5,606	3.12	49.48	achieved	2,874	2.45	31.85
All		179,108				117,137		
Panel B: Most common negative words								
1	contract	8,865	6.75	6.75	loss	4,145	5.22	5.22
2	object	8,224	6.26	13.01	losses	2,835	3.57	8.80
3	limit	7,037	5.36	18.37	against	2,550	3.21	12.01
4	loss	6,980	5.32	23.69	challenges	2,447	3.08	15.09
5	liquid	4,204	3.20	26.89	claims	1,890	2.38	17.48
6	challeng	3,474	2.65	29.54	conflict	1,499	1.89	19.36
7	sever	3,273	2.49	32.03	impairment	1,485	1.87	21.24
8	subject	3,011	2.29	34.32	exposed	1,469	1.85	23.09
9	claim	2,662	2.03	36.35	negative	1,123	1.42	24.50
10	against	2,550	1.94	38.29	weaknesses	975	1.23	25.73
All		131,928				80,869		
Panel C: Most common uncertain words								
1	risk	37,614	45.88	45.88	risk	27,995	33.66	33.66
2	may	13,655	16.66	62.54	risks	17,901	21.52	55.18
3	condit	4,524	5.52	68.06	may	13,655	16.42	71.60
4	differ	3,222	3.93	71.99	could	2,015	2.42	74.02
5	possibl	2,459	3.00	74.99	possible	1,887	2.27	76.29
6	exposur	2,229	2.72	77.71	exposure	1,807	2.17	78.46
7	could	2,015	2.46	80.17	approximately	926	1.11	79.57
8	believ	1,618	1.97	82.14	believes	918	1.10	80.68
9	fluctuat	1,486	1.81	83.95	precautionary	867	1.04	81.72
10	suggest	1,391	1.70	85.65	fluctuations	851	1.02	82.74
All		85,088				86,033		

The table compares the similarity of sentiment classification across negative, positive, and uncertain categories, as identified in English annual reports using different word representation techniques. The occurrences of the English words were identified using the Loughran and McDonald (LM) Dictionary. The stemmed LM dictionary version was created using the Porter stemmer (Porter, 1980).

Table B.3 (a-2) English vs. English (stemmed) Annual reports textual sentiment analysis

English						English (stemmed)					Pairwise Corr.	Spearman Corr.
	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)		
POS	2.17	2.03	0.97	0.23	5.79	3.54	3.41	1.04	1.33	7.19	0.939***	0.936***
NEG	1.65	1.51	0.68	0.35	5.19	2.74	2.59	0.83	1.09	6.76	0.884***	0.885***
UNC	1.85	1.72	0.83	0.24	6.15	1.87	1.76	0.83	0.32	7.09	0.965***	0.966***

The table shows a summary statistic of sentiment words in English annual reports using different word representation techniques based on Loughran and McDonald's (2011) (LM dictionary). The English stem extraction was performed using Porter Stemmer (1980). Additionally, this table displays simple pairwise correlations and Spearman rank correlations. These correlations relate to negative, positive, and uncertain word lists from the LM dictionary (inflected vs. stemmed). ***, **, and * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B.3 (b-1) Most Frequent Sentiment Words Occurring in Arabic Annual Reports

Rank	**lemmatized word form**				**Stemmed word forms**			
	Word	Total	%	Cum%	Word	Total	%	Cum%
Panel A: Most common positive words								
1	تَحْقِيق	16,828	5.86	5.86	شرك	199,941	21.01	21.01
2	تَطْوِير	15,819	5.51	11.36	حقق	44,269	4.65	25.67
3	نُمُوّ	11,890	4.14	15.50	نظم	44,178	4.64	30.31
4	تَعْزِيز	11,499	4.00	19.51	بني	38,674	4.06	34.38
5	دَعْم	9,777	3.40	22.91	كفأ	38,398	4.04	38.41
6	قُدْرَة	9,434	3.28	26.19	سعد	31,088	3.27	41.68
7	تَحْسِين	8,875	3.09	29.28	طور	28,273	2.97	44.65
8	ضَمان	8,431	2.93	32.22	قرر	27,390	2.88	47.53
9	كَفاءَة	7,015	2.44	34.66	أمن	26,315	2.77	50.29
10	أَعْلَى	6,627	2.31	36.97	ثمر	23,902	2.51	52.81
All		282,927				946,741		
Panel B: Most common negative words								
1	خَسارَة	7,431	5.86	5.86	عوم	55,279	6.45	6.45
2	اِنْخِفاض	5,079	4.01	9.87	جرأ	33,339	3.89	10.34
3	تَحَدِّي	3,407	2.69	12.55	حدد	32,161	3.75	14.10
4	تَعْوِيض	2,904	2.29	14.84	خلل	26,097	3.05	17.14
5	تَقْلِيل	2,744	2.16	17.01	بلغ	25,471	2.97	20.12
6	خَضَع	2,037	1.61	18.62	طلب	23,530	2.75	22.86
7	سَلْبِيّ	1,983	1.56	20.18	لزم	20,463	2.39	25.25
8	تَخْفِيض	1,686	1.33	21.51	شكل	18,461	2.15	27.41
9	عارَض	1,655	1.31	22.81	صدر	17,398	2.03	29.44
10	مُواجَهَة	1,545	1.22	24.03	نهي	17,110	2.00	31.43
All		139,645				1,231,535		
Panel C: Most common uncertain words								
1	مَخاطِر	44,938	51.97	51.97	حسب	21,915	15.33	15.33
2	مُتَوَقَّع	4,586	5.30	57.28	رقب	19,211	13.44	28.76
3	مُقْتَرَح	2,995	3.46	60.74	تبع	18,101	12.66	41.42
4	تَعَرَّض	2,684	3.10	63.84	وقع	17,188	12.02	53.45
5	مُحْتَمَل	2,677	3.10	66.94	كل	11,661	8.16	61.60
6	تَوَقَّع	2,662	3.08	70.02	بدأ	11,470	8.02	69.62
7	قَدَّر	2,353	2.72	72.74	فرق	6,221	4.35	73.97
8	مُتَغَيِّر	1,749	2.02	74.76	قرح	5,888	4.12	78.09
9	مَعْقُول	1,579	1.83	76.59	نظر	5,223	3.65	81.75
10	إِيضاح	1,406	1.63	78.21	شرط	4,497	3.15	84.89
All		104,580				522,085		

The table compares the similarity of sentiment classification across negative, positive, and uncertain categories, as identified in Arabic annual reports using different word representation techniques. The occurrences of the Arabic words were identified using the ArFinSD. The Arabic stem extraction was performed using Khoja Arabic Stemmer (Khoja and Garside, 1999)

Table B.3 (b-2) Arabic vs. Arabic (stemmed) Annual reports textual sentiment analysis

Arabic						Arabic (stemmed)					Pairwise Corr.	Spearman Corr.
	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)		
POS	4.20	3.82	1.70	0.89	10.52	16.25	16.44	2.02	8.05	21.89	0.511***	0.488***
NEG	2.34	2.21	0.74	0.50	5.47	20.89	20.54	2.06	11.93	30.51	0.708***	0.670***
UNC	1.80	1.71	0.66	0.08	4.03	9.09	8.95	1.34	5.03	13.73	0.770***	0.754***

The table shows a summary statistic of sentiment words in Arabic annual reports using different word representation techniques based Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic stem extraction was performed using Khoja Arabic Stemmer (Khoja and Garside, 1999). The ArFinSD was converted into a stemmed version using the lemmatized version entries. Additionally, this table displays simple pairwise correlations and Spearman rank correlations. These correlations relate to negative, positive, and uncertain word lists from the ArFinSD dictionary (lemmatized vs. stemmed). ***, **, and * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B.3 (a-3) English (stemmed) vs. Arabic (stemmed) Annual reports textual sentiment analysis

English (stemmed)						Arabic (stemmed)					Pairwise Corr.	Spearman Corr.
	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)		
POS	3.54	3.41	1.04	1.33	7.19	16.25	16.44	2.02	8.05	21.89	0.500***	0.643***
NEG	2.74	2.59	0.83	1.09	6.76	20.89	20.54	2.06	11.93	30.51	0.616***	0.621***
UNC	1.87	1.76	0.83	0.32	7.09	9.09	8.95	1.34	5.03	13.73	0.666***	0.660***

The table shows a summary statistic of stemmed sentiment words in English annual reports and their corresponding Arabic versions based on the Loughran and McDonald (2011) (LM) dictionary and the Arabic Financial Sentiment Dictionary (ArFinSD). The English stem extraction was performed using Porter Stemmer (1980). The Khoja stemmer (1999) was used to extract the word stem form in Arabic. Additionally, the correlations relate to negative, positive, and uncertain words identified in the stemmed version of the sentiment dictionaries. The ArFinSD was converted into a stemmed version using the lemmatized version entries.

Appendix B.4 - Stop Word Lists (Arabic and English)

Table B.4 (a-1) Geographies Arabic Stop Words				
شارع	مدينة	دولة	محافظة	قارة
آسيا	استراليا	إفريقيا	أمريكا	روسيا
أوروبا	السعودية	الرياض	جدة	مكة
المدينة المنورة	الدمام	الهنوف والمبرز	الطائف	تبوك
بريدة	خميس مشيط	الجبيل	عسير	حائل
نجران	حفر الباطن	أبها	الثقبة	السيحب
بينبع	الخبر	عرعر	عنيزة	سكاكا
الجوف	الحوية	جيزان	جازان	الظهران
القطيف	القريات	الباحة	وادي الدواسر	الرس
بيشة	تاروت	سيهات	شرورة	بحرة
الخفجي	صبيا	الدوادمي	أبو عريش	الزلفي
أحد رفيدة	رابغ	رأس تنورة	رفحاء	صفوى
طبرجل	طريف	المجمعة	البدائع	القصيم
عفيف	بلجرشي	الدرعية	الدلم	أملج
بقيق	العيون	دومة الجندل	صامطة	العلا
ليلى	بيش	الوجه	تيماء	المزاحمية
البكيرية	بدر	القديح	الخرمة	النماص
العويمة	شقراء	السليل	النعيرية	حوطة بني تميم
تربة	حقل	الجموم	ضباء	أحد المسارحة
القنفذة	ضمد	ظهران الجنوب	الطرف	القوز
عنك	القيصومة	القويعية	المخواة	رنية
رماح	العلاية	حوطة سدير	الليث	المنيزلة
العمران	الشرقية	رياض الخبراء	الحاير	الحناكية
خيبر	العقيق	تنومة	العويقلية	فرسان
بقعاء	أم الساهك	قلوة	عرقة	الجشة
مرات	ضرما	العيص	الهياثم	جعرانة
الأحساء	حلة محيش	الجفر	حريملاء	تمير
الرميلية	الدرب	الهدا	البديع والقرفي	العالية والخضراء
الجرن	الخويلدية	المظيلف	الحريق	التوبي
تثليث	الاثنين	العيدابي	المطعن	ثادق
البديع الشمالي	ذهبان	الحائط	المليداء	المركز
العارضة	مسلية	عين بن فهيد	الحوطة	الرويضة
المطيرفي	صعبر السفران	بحر أبو سكينة	بئر بن هرماس	مليجة
الشماسية	الدليمية	اليمامة	رخية	تبالة
الخضراء	الملاحة	الفويلق	روضة هباس	القوارة
الضبيعة	تصلال	السديرة	نعجان	اللقية
الذيبية	البحرين	الكويت	عمان	الإمارات
قطر	العراق	الأردن	اليمن	مصر
السودان	لبنان	إيران	تركيا	المنامة
سلطنة عمان	بيروت	الخرطوم	بغداد	الدوحة
أبو ظبي	صنعاء	القاهرة	واشنطن	ألمانيا
برلين	فرنسا	باريس	موسكو	اليابان
أفغانستان	باكستان	أذربيجان	بيلاروس	بليز
طوكيو	أستراليا	كندا	بريطانيا	لندن
الصين	بكين	الهند	دلهي	جزر القمر
جمهورية الكونغو الديمقراطية	سويسرا	تشيلي	كولومبيا	كوستاريكا
كوبا	جزر الرأس الأخضر	تشيكوسلوفاكيا	غيبوتي	الدنمارك

Table B.4 (a-1) Geographies Arabic Stop Words				
دومينيكا	الجزائر	استونيا	إريتريا	أثيوبيا
أوروبا	أسبانيا	فنزويلا	فوكلاند	روندا
جورجيا	جيرنسي	جبل طارق	جامبيا	غينيا الجديدة
جواتيمالا	جويانا	هونغ كونغ	الهندوراس	كرواتيا
هايتي	المجر	أندونيسيا	إسرائيل	جزيرة مان
الهند	ايسلندا	المملكة المتحدة	جاميكا	اليابان
كينيا	جزر سليمان	كمبوديا	كوريا الشمالية	كوريا الجنوبية
جزر كايمان	كازاخستان	لاروس	مقدونيا	سريلانكا
ليبيريا	ليبيا	المغرب	فيتنام	السويد
سنغافورا	الصومال	سورينام	سلفادور	سوريا
تايلاند	منغوليا	تونس	تنزانيا	المالديف
أوكرانيا	المكسيك	ماليزيا	موزمبيق	ناميبيا
نيجيريا	أوغندا	النرويج	نيبال	نيوزيلندا
زيمبابوي	جنوب أفريقيا	الفلبين	بولندا	أوزباكستان
رومانيا	روسيا	الصرب		

Table B.4 (a-2) Number and Dates Arabic Stop Words				
ألف	مليون	بليون	ترليون	سنوي
سنة	ربعي	بشكل ربعي	شهر	شهري
أسبوع	أسبوعي	يناير	فبراير	مارس
ابريل	مايو	يونيو	يوليو	أغسطس
سبتمبر	أكتوبر	نوفمبر	ديسمبر	كانون الثاني
شباط	آذار	نيسان	أيار	حزيران
تموز	آب	أيلول	تشرين الأول	تشرين الثاني
كانون الأول	صَفَر	ربيع الأول	ربيع الآخر	جمادى الأولى
جمادى الآخرة	رجب	شعبان	رمضان	شوال
ذو القعدة	ذو الحجة	الأثنين	الثلاثاء	الأربعاء
الخميس	الجمعة	الأحد	السبت	واحد
اثنان	ثلاثة	أربعة	خمسة	ستة
سبعة	ثمانية	تسعة	عشرة	أحد عشر
اثنا عشر	ثلاثة عشر	أربعة عشر	خمسة عشر	ستة عشر
سبعة عشر	ثمانية عشر	تسعة عشر	عشرون	واحد وعشرون
اثنان وعشرون	ثلاثة وعشرون	أربعة وعشرون	خمسة وعشرون	ستة وعشرون
سبعة وعشرون	ثمانية وعشرون	تسعة وعشرون	ثلاثون	واحد وثلاثون
اثنان وثلاثون	ثلاثة وثلاثون	أربعة وثلاثون	خمسة وثلاثون	ستة وثلاثون
سبعة وثلاثون	ثمانية وثلاثون	تسعة وثلاثون	أربعون	واحد وأربعون
اثنان وأربعون	ثلاثة وأربعون	أربعة وأربعون	خمسة وأربعون	ستة وأربعون
سبعة وأربعون	ثمانية وأربعون	تسعة وأربعون	خمسون	واحد وخمسون
اثنان وخمسون	ثلاثة وخمسون	أربعة وخمسون	خمسة وخمسون	ستة وخمسون
سبعة وخمسون	ثمانية وخمسون	تسعة وخمسون	ستون	واحد وستون
اثنان وستون	ثلاثة وستون	اربعة وستون	خمسة وستون	ستة وستون
سبعة وستون	ثمانية وستون	تسعة وستون	سبعون	واحد وسبعون
اثنان وسبعون	ثلاثة وسبعون	أربعة وسبعون	خمسة وسبعون	ستة وسبعون
سبعة وسبعون	ثمانية وسبعون	تسعة وسبعون	ثمانون	واحد وثمانون
اثنان وثمانون	ثلاث وثمانون	أربعة وثمانون	خمسة وثمانون	ستة وثمانون
سبعة وثمانون	ثمانية وثمانون	تسعة وثمانون	تسعون	واحد وتسعون
اثنان وتسعون	ثلاثة وتسعون	اربعة وتسعون	خمسة وتسعون	ستة وتسعون
سبعة وتسعون	ثمانية وتسعون	تسع وتسعون	مئه	I
II	III	IV	V	VI

Table B.4 (a-2) Number and Dates Arabic Stop Words				
VII	VIII	IX	X	XI
XII	XIII	XIV	XV	XVI
XVII	XVIII	XIX	XX	XXI
XXII	XXIII	XXIV	XXX	XL
L	LX	LXX	LXXX	XC
C	CI	CII	CC	CCC
CD	D	DC	DCC	DCCC
CM	M	MI	MII	MIII
MCM	MM	MMI	MMII	MMC
MMM	MMMM	V		

The English stop word was initially obtained from the official Loughran–McDonald textual analysis resources. The list was translated into Arabic by the author and expanded to include Hijri (Islamic) calendar month names. Source: https://sraf.nd.edu/textual-analysis/.

Table B.4 (a-3) Currency and Country Arabic Stop Words			
Currency	Country	Currency	Country
ريال سعودي	السعودية	الكورون التشيكي	تشيكوسلوفاكيا
الدرهم الإماراتي	الإمارات	الفرنك الجيبوتي	غيبوتي
ريال قطري	قطر	الكرون الدانماركي	الدنمارك
دينار بحريني	البحرين	البيزو الدومينيكي	دومينيكا
جنيه مصري	مصر	الدينار الجزائري	الجزائر
الأفغاني الأفغانستاني	أفغانستان	الكرون الإستوني	استونيا
الليك الألباني	ألبانيا	الناكفا الإريترية	إريتريا
الدرام الأرميني	أرمينيا	البير الأثيوبي	أثيوبيا
الجيلدر الهولندي	هولندا	اليورو	ألمانيا
الكوانزا الأنجولية	انغولا	اليورو	أوروبا
البيزو الأرجنتيني	الأرجنتين	اليورو	أسبانيا
الدولار الاسترالي	أستراليا	الدولار الفيجي	فنزويلا
ريال يمني	اليمن	جنيه جزيرة فوكلاند	فوكلاند
المانات الأذربيجاني	أذربيجان	الفرنك الرواندي	روندا
المارك القابل للتحويل	البوسنة والهرسك	اللاري الجورجي	جورجيا
الدولار البارابادوسي	باربادوس	الجنيه الجيرنسي	جيرنسي
بيتكوين	عملة رقمية عالمية	السيدي الغاني	غانا
التاكا البنجلاديشية	بنغلادش	جنيه جبل طارق	جبل طارق
الليف البلغاري	بلغاريا	الدالاسي الجامبي	جامبيا
الدينار الأردني	الأردن	الفرنك الغيني	غينيا الجديدة
الفرنك البوروندي	بوروندي	الكتزل الجواتيمالي	جواتيمالا
الدولار البرمودي	برمودا	الدولار الجوياني	جويانا
الدولار البروني	بروناي	دولار هونج كونج	هونغ كونغ
البوليفيانو البوليفي	بوليفيا	اللامبيرا الهندوراسي	الهندوراس
الريال البرازيلي	البرازيل	الكونا الكرواتية	كرواتيا
الدولار الباهامي	جزر البهاما	الجورد الهايتي	هايتي
اليورو	اليونان	الفورنت المجري	المجر
البولا البوتسوانية	بوتسوانا	الروبية الأندونيسية	أندونيسيا
الروبل البلاروسية	بيلاروس	الشيكل الإسرائيلي	إسرائيل

Table B.4 (a-3) Currency and Country Arabic Stop Words			
الدولار البليزي	بليز	جنيه جزيرة مانكس	جزيرة مان
الدولار الكندي	كندا	الروبية الهندية	الهند
الفرنك الكنغولي	جمهورية الكونغو الديمقراطية	الدينار العراقي	العراق
الفرنك السويسري	سويسرا	الريال الإيراني	إيران
البيزو الشيلي	تشيلي	الكرونا الأيسلندية	ايسلندا
اليوان الرينمنبي الصيني	الصين	الجنيه الإسترليني	المملكة المتحدة
البيزو الكولومبي	كولومبيا	البيزو القابل للتحويل الكوبي	كوبا
الكولون الكوستاريكي	كوستاريكا	إسكيدو الرأس الأخضر	جزر الرأس الأخضر
الدولار الجاميكي	جاميكا	البيزو المكسيكي	المكسيك
البوليفار الفنزويلي	فنزويلا	الرينجت الماليزي	ماليزيا
الين الياباني	اليابان	المتكال الموزمبيقي	موزمبيق
الشلن الكيني	كينيا	الدولار الناميبي	ناميبيا
دولار جزر سليمان	جزر سليمان	النيرة النيجيرية	نيجيريا
الريال الكمبودي	كمبوديا	الشلن الأوغندي	أوغندا
الفرنك القمري	جزر القمر	الكرون النرويجي	النرويج
الوون الكوري الشمالي	كوريا الشمالية	الروبي النيبالي	نيبال
الوون الكوري الجنوبي	كوريا الجنوبية	الدولار النيوزيلندي	نيوزيلندا
الدينار الكويتي	الكويت	الريال العماني	عمان
الدولار الكايماني	جزر كايمان	الدولار الزيمبابوي	زيمبابوي
التنج الكازاخستاني	كازاخستان	الدولار الأمريكي	أمريكا
الكيب اللاروسي	لاروس	الراند الجنوب أفريقي	جنوب أفريقيا
الجنيه اللبناني	لبنان	البيزو الفلبيني	الفلبين
الدينار المقدوني	مقدونيا	الروبية الباكستانية	باكستان
الروبية السريلانكية	سريلانكا	الزلوتي البولندي	بولندا
الدولار الليبيري	ليبيريا	السوم الأوزباكستاني	أوزباكستان
الدينار الليبي	ليبيا	الليو الجديد الروماني	رومانيا
الدرهم المغربي	المغرب	الروبل الروسي	روسيا
الدونغ الفيتنامي	فيتنام	الدينار الصربي	الصرب
الجنيه السوداني	السودان	الليرة السورية	سوريا
الكرونا السويدية	السويد	البات التايلاندي	تايلاند
الدولار السنغافوري	سنغافورا	التوغريك المنغولي	منغوليا
الشلن الصومالي	الصومال	الدينار التونسي	تونس
الدولار السورينامي	سورينام	الليرة التركية	تركيا
الكولون السلفادوري	سلفادور	الشلن التنزاني	تنزانيا
هيرفانا أوكرانية	أوكرانيا	الروفيا المالديفية	المالديف

The English stop word was initially obtained from the official Loughran–McDonald textual analysis resources. The list was translated into Arabic by the author. Source: https://sraf.nd.edu/textual-analysis/.

Table B.4 (a-4) Arabic Financial Job Titles Stop Words

مدير مالي	مدير إدارة الأصول الاستثمارية الدولية	مسؤول التنظيم المالي
مدير حسابات	محلل تحليلات الأوراق المالية الدولية	مسؤول الإصدارات المالية
محاسب مالي	مدير إدارة الأعمال المالية	مسؤول الإدارة الإصدارات المالية
مراقب مالي	محلل تحليلات الأسهم المحلية	مسؤول الإدارة الإصدارات الخاصة
محلل مالي	مدير إدارة الأصول الاجتماعية الدولية	مسؤول الخزينة
محلل ائتمان	مسؤول الإحصاءات المالية	مسؤول التدقيق المالي
مسؤول خدمة العملاء	مدير إدارة الأصول الثابتة الدولية	مسؤول التصريحات المالية
أمين خزنة	محلل تحليلات الأوراق المالية الثابتة	مسؤول الضرائب
مسؤول تخطيط ومتابعة	مدير إدارة الأصول الخدمية الدولية	مسؤول الإدارة المالية الدولية
مستشار مالي	مدير بنك	مسؤول الأعمال الخاصة المالية
مسؤول علاقات المستثمرين	مسؤول حسابات	مسؤول الإشعارات المالية الدولية
مستشار إداري	مسؤول تأمين	مسؤول التوزيع المالي
محصل مالي	مسؤول التداولات	مسؤول التخطيط المالي الدولي
مسؤول ميزانية	مسؤول التأمين الآجل	مدير إدارة المؤسسات المالية
مسؤول إدارة مخاطر	مسؤول التأمين الشخصي	محلل تحليلات الأسهم
مدير تحليلات مالية	مسؤول التمويل	مدير إدارة الأصول الثابتة
مدير إدارة الأصول	مسؤول الإدارة المالية	مدير إدارة الأصول الخدمية
محلل سوق الأوراق المالية	مسؤول الائتمان	محلل تحليلات الأوراق المالية
مدير توزيع الأرباح	مسؤول خدمة الزبائن الحرة	مدير تحليلات السوق
مدير تداول الأسهم	مسؤول تخطيط الأعمال	محلل سوق الأوراق المالية المتداولة
مدير تداول العملات الرقمية	مسؤول الاستثمار	مدير إدارة الأصول النقدية
مدير إدارة الأصول الأخرى	مسؤول خدمة الأعمال التجارية	محلل تحليلات الأسهم العالمية
مدير تخطيط الأعمال المالية	مسؤول الإصدارات الآجلة	مدير إدارة الأصول الاستثمارية
مستشار تخطيط الأعمال المالية	مسؤول المؤسسات الخاصة	مدير تحليلات الأسواق العالمية
مدير إدارة الأصول الاجتماعية	مسؤول الأعمال الدولية	وزير المالية
محلل إدارة الأصول	مسؤول خدمة الأعمال الخاصة	رئيس إدارة المالية
مدير إدارة الأعمال	مسؤول الإشعارات المالية	مسؤول التخطيط المالي
		محلل تحليلات الأوراق المالية الاجتماعية

The English stop word was initially obtained from the official Loughran–McDonald textual analysis resources. The list was translated into Arabic by the author. Source: https://sraf.nd.edu/textual-analysis/.

Table B.4 (a-5) Arabic Company Long Name Stop Words	
شركة كيمائيات الميثانول	البنك السعودي للإستثمار
الشركة السعودية للصناعات الأساسية	البنك السعودي الفرنسي
شركة سابك للمغذيات الزراعية	البنك العربي الوطني
شركة التصنيع الوطنية	مصرف الراجحي
شركة اللجين	بنك البلاد
شركة نماء للكيماويات	مصرف الإنماء
المجموعة السعودية للإستثمار الصناعي	البنك الأهلي السعودي
شركة ينبع الوطنية للبتروكيماويات	شركة أملاك العالمية للتمويل
شركة الصحراء العالمية للبتروكيماويات	البنك السعودي البريطاني
الشرقية للتنمية	صندوق الرياض ريت
شركة كيان السعودية للبتروكيماويات	صندوق مشاركة ريت
شركة أسمنت حائل	صندوق جدوى ريت السعودية
شركة أسمنت نجران	صندوق ميفك ريت
شركة أسمنت المدينة	صندوق سدكو كابيتال ريت
شركة أسمنت المنطقة الشمالية	صندوق المعذر ريت
شركة أسمنت ام القرى	صندوق الأهلي ريت 1
شركة الأسمنت العربية	صندوق دراية ريت
شركة أسمنت اليمامة	صندوق بنيان ريت
شركة الأسمنت السعودية	صندوق جدوى ريت الحرمين
شركة أسمنت المنطقة الجنوبية	صندوق الراجحي ريت
شركة أسمنت ينبع	صندوق الخبير ريت
شركة أسمنت المنطقة الشرقية	صندوق الجزيرة ريت
شركة أسمنت تبوك	الشركة العربية للتعهدات الفنية
شركة أسمنت الجوف	شركة تهامة للإعلان والعلاقات العامة
شركة الكثيري القابضة	المجموعة السعودية للأبحاث والإعلام
شركة مكة للإنشاء والتعمير	شركة البحر الأحمر العالمية
شركة الصناعات الكيميائية الأساسية	الشركة العقارية السعودية
شركة التعدين العربية السعودية	شركة الأندلس العقارية
شركة زهرة الواحة للتجارة	شركة المراكز العربية
شركة الشرق الأوسط لصناعة وإنتاج الورق	شركة طيبة للإستثمار
شركة الصناعات الزجاجية الوطنية	شركة التأمين العربية التعاونية
شركة تصنيع مواد التعبئة والتغليف	شركة الغاز والتصنيع الأهلية
الشركة الوطنية لتصنيع وسبك المعادن	شركة الزيت العربية السعودية
الشركة السعودية لصناعة الورق	الشركة الوطنية السعودية للنقل البحري
شركة إتحاد مصانع الأسلاك	بنك الرياض
الشركة السعودية لأنابيب الصلب	بنك الجزيرة
شركة الجبس الأهلية	شركة الرياض للتعمير
الشركة العربية للأنابيب	إعمار المدينة الاقتصادية
شركة الزامل للإستثمار الصناعي	شركة جبل عمر للتطوير
شركة رابغ للتكرير والبتروكيماويات	شركة دار الأركان للتطوير العقاري
شركة الدريس للخدمات البترولية والنقليات	مدينة المعرفة الإقتصادية
الشركة السعودية للخدمات الصناعية	الشركة السعودية للتسويق
شركة ذيب لتأجير السيارات	مجموعة أنعام الدولية القابضة
الشركة السعودية للخدمات الأرضية	شركة عبد الله سعد أبو معطي للمكتبات
الشركة السعودية للنقل الجماعي	شركة باعظيم التجارية

Table B.4 (a-5) Arabic Company Long Name Stop Words	
شركة باتك للإستثمار والأعمال اللوجستية	الشركة المتحدة للإلكترونيات
الشركة المتحدة الدولية للمواصلات	الشركة السعودية لخدمات السيارات والمعدات
الشركة العربية لخدمات الإنترنت والاتصالات	شركة جرير للتسويق
شركة عِلم	شركة فواز عبدالعزيز الحكير وشركاه
شركة المعمر لأنظمة المعلومات	الشركة السعودية للعدد والأدوات
شركة بحر العرب لأنظمة المعلومات	شركة الحسن غازي إبراهيم شاكر
شركة إتحاد إتصالات	شركة العمران للصناعة والتجارة
شركة الإتصالات المتنقلة السعودية	مجموعة أسترا الصناعية
شركة إتحاد عذيب للإتصالات	الشركة السعودية للصادرات الصناعية
شركة الإتصالات السعودية	شركة بوان
شركة الخطوط السعودية للتموين	شركة الصناعات الكهربائية
شركة مهارة للموارد البشرية	شركة الخزف السعودي
الشركة السعودية للطباعة والتغليف	شركة الكابلات السعودية
شركة صدر للخدمات اللوجستية	شركة أميانتيت العربية السعودية
مجموعة صافولا	شركة البابطين للطاقة والإتصالات
شركة تكوين المتطورة للصناعات	الشركة السعودية لإنتاج الأنابيب الفخارية
الشركة السعودية لمنتجات الألبان والأغذية	شركة الشرق الأوسط للكابلات المتخصصة
الشركة السعودية للصناعات المتطورة	شركة لجام للرياضة
شركة المراعي	شركة ريدان الغذائية
شركة حلواني إخوان	شركة الخليج للتدريب والتعليم
الشركة المتقدمة للبتروكيماويات	شركة هرفي للخدمات الغذائية
شركة القصيم القابضة للاستثمار	مجموعة سيرا القابضة
الشركة السعودية للأسماك	شركة المشروعات السياحية
شركة الجوف الزراعية	شركة دور للضيافة
شركة أكوا باور	شركة لازوردي للمجوهرات
شركة الخريف لتقنية المياه والطاقة	شركة ثوب الأصيل
الشركة السعودية للكهرباء	مجموعة فتيحي القابضة
مجموعة بن داود القابضة	شركة نسيج العالمية التجارية
شركة النهدي الطبية	شركة العبداللطيف للإستثمار الصناعي
شركة أسواق عبدالله العثيم	شركة الإنماء طوكيو مارين
الشركة السعودية لإعادة التأمين	شركة الراجحي للتأمين التعاوني
الشركة العالمية للتأمين التعاوني	شركة عناية السعودية للتأمين التعاوني
شركة بروج للتأمين التعاوني	شركة تُشب العربية للتأمين التعاوني
الشركة الخليجية العامة للتأمين التعاوني	شركة الصقر للتأمين التعاوني
مجموعة الخليج للتأمين	شركة بوبا العربية للتأمين التعاوني
شركة أمانة للتأمين التعاوني	الشركة المتحدة للتأمين التعاوني
الشركة الوطنية للتأمين	شركة ثمار التنمية القابضة
شركة الاتحاد للتأمين التعاوني	مجموعة عبدالمحسن الحكير للسياحة والتنمية
المجموعة المتحدة للتأمين التعاوني	شركة الباحة للإستثمار والتنمية
شركة إتحاد الخليج الأهلية للتأمين التعاوني	الشركة السعودية للتنمية الصناعية
الشركة العربية السعودية للتأمين التعاوني	شركة النايفات للتمويل
شركة الدرع العربي للتأمين التعاوني	شركة المملكة القابضة
شركة ولاء للتأمين التعاوني	شركة الدواء للخدمات الطبية
شركة سلامة للتأمين التعاوني	الشركة السعودية لتمويل المساكن
شركة أليانز السعودي الفرنسي للتأمين التعاوني	شركة المصانع الكبرى للتعدين

Table B.4 (a-5) Arabic Company Long Name Stop Words	
الشركة التعاونية للتأمين	صندوق سيكو السعودية ريت
شركة الجزيرة تكافل تعاوني	صندوق تعليم ريت
شركة ملاذ للتأمين التعاوني	شركة رتال للتطوير العمراني
شركة المتوسط والخليج للتأمين وإعادة التأمين التعاوني	شركة أمريكانا للمطاعم العالمية بي إل سي
شركة الشرق الأوسط للرعاية الصحية	شركة مجموعة تداول السعودية القابضة
مجموعة الدكتور سليمان الحبيب للخدمات الطبية	صندوق الإنماء ريت لقطاع التجزئة
شركة المواساة للخدمات الطبية	صندوق ملكية عقارات الخليج ريت
شركة الحمادي القابضة	شركة وفرة للصناعة والتنمية
شركة دله للخدمات الصحية	شركة التنمية الغذائية
الشركة الوطنية للرعاية الطبية	الشركة الوطنية للتنمية الزراعية
شركة أيان للإستثمار	شركة تبوك للتنمية الزراعية
الشركة الكيميائية السعودية القابضة	شركة الشرقية للتنمية
شركة دار المعدات الطبية والعلمية	شركة جازان للطاقة والتنمية
الشركة السعودية للصناعات الدوائية والمستلزمات الطبية	شركة سناد القابضة

Table B.4 (a-6) Arabic Company Short Name Stop Words			
كيمانول	أنابيب السعودية	العقارية	الجوف
سابك	جبسكو	الأندلس	جازادكو
سابك للمغذيات الزراعية	أنابيب	سينومي سنترز	أكوا باور
التصنيع	الزامل للصناعة	طيبة	الخريف
اللجين	بترو رابغ	مكة	كهرباء السعودية
نماء للكيماويات	الدريس	إعمار	بن داود
المجموعة السعودية	الغاز	جبل عمر	النهدي
ينساب	أرامكو السعودية	دار الأركان	أسواق ع العثيم
سبكيم العالمية	البحري	مدينة المعرفة	أسواق المزرعة
كيان السعودية	الرياض	سيسكو	ثمار
أسمنت حائل	الجزيرة	ذيب	أنعام القابضة
أسمنت نجران	الاستثمار	الخدمات الأرضية	أبو معطي
أسمنت المدينة	السعودي الفرنسي	سابتكو	باعظيم
أسمنت الشمالية	العربي	باتك	إكسترا
أسمنت ام القرى	الراجحي	بدجت السعودية	ساسكو
أسمنت العربية	البلاد	سلوشنز	جرير
أسمنت اليمامة	الإنماء	عِلم	سينومي ريتيل
أسمنت السعودية	الأهلي	إم آي إس	ساكو
أسمنت الجنوبية	أملاك	بحر العرب	الحسن شاكر
أسمنت ينبع	ساب	إتحاد إتصالات	العمران
أسمنت الشرقية	الرياض ريت	زين السعودية	أسترا الصناعية
أسمنت تبوك	مشاركة ريت	عذيب للإتصالات	بوان
أسمنت الجوف	جدوى ريت السعودية	اس تي سي	الصناعات الكهربائية
الكثيري	ميفك ريت	التموين	الخزف السعودي
تكوين	سدكو كابيتال ريت	طباعة وتغليف	الكابلات
بي سي آي	المعذر ريت	صدر	أميانتيت
معادن	الأهلي ريت	صافولا	البابطين

Table B.4 (a-6) Arabic Company Short Name Stop Words

الواحة	دراية ريت	سدافكو	الفخارية
مبكو	بنيان ريت	المراعي	مسك
زجاج	جدوى ريت الحرمين	حلواني إخوان	وقت اللياقة
فيبكو	الراجحي ريت	نادك	ريدان الغذائية
معدنية	الخبير ريت	جاكو	الخليج للتدريب
صناعة الورق	الجزيرة ريت	تبوك الزراعية	هرفي للأغذية
أسلاك	العربية	الأسماك	سيرا
الأصيل	مجموعة الحكير	الإنماء طوكيو	الوطنية
مجموعة فتيحي	شمس	تكافل الراجحي	التأمين العربية
نسيج	دور	عناية	أسيج
العبداللطيف	لازوردي	ثشب	إتحاد الخليج الأهلية
تهامة للإعلان	سلامة	الصقر للتأمين	سايكو
الأبحاث والإعلام	أليانز إس إف	بوبا العربية	الدرع العربي
البحر الأحمر	جزيرة تكافل	المتحدة للتأمين	ولاء للتأمين
المملكة	ملاذ للتأمين	الإعادة السعودية	دله الصحية
الدواء	ميدغلف للتأمين	العالمية	رعاية
أماك	السعودي الألماني الصحية	بروج للتأمين	أيان للاستثمار
سيكو السعودية ريت	سليمان الحبيب	الخليجية العامة	الكيميائية
تعليم ريت	المواساة	جي آي جي	دار المعدات
رتال	الحمادي	أمانة للتأمين	الدوائية
مطاعم أمريكانا	صدق	الإنماء ريت للتجزئة	سناد القابضة
الباحة	مجموعة تداول	ملكية ريت	النايفات

Table B.4 (a-7) Arabic Generic Stop Words

words						
حول	هنا	خاص	كان	فعل	معظم	بين
فوق	لها	نفس	نحن	يفعل	نفسي	كلا
بعد	نفسها	هي	كانوا	يجرى	الآن	ولكن
مرة أخرى	له	يجب	ماذا	أسفل	من	بواسطة
الكل	نفسه	حتى	متى	أثناء	على	هناك
أكون	له	بعض	أين	كل	مرة واحدة	هذه
بين	كيف	مثل	أي	قليل	فقط	هذا
و	إذاً	من	بينما	إلى	أو	تلك
أي	إلى	ذلك	من	من	آخر	من خلال
هي	هو	لهم	مع من	إضافي	لنا	إلى
كما	له	أنفسهم	لماذا	كان لديه	أنفسنا	أيضاً
يكون	نفسه	ثم	مع	لديه	خارج	تحت
لأن	فقط	نفسك	أنت	يملك	لها	حتى
قبل	لي	أنفسكم	لك	هو	أكثر	جداً

The English stop word was initially obtained from the official Loughran–McDonald textual analysis resources. The list was translated into Arabic by the author. Source: https://sraf.nd.edu/textual-analysis/.

Table B.4(b-1) Geographies English Stop Words			
street	Al-Qatif	Badr	Qilwah
City	Qurayyat	Qudaih	Irqah
State	Al Bahah	Al Khurma	Al Jishah
Governorate	Wadi Al Dawasir	Al Namas	Marat
continent	Ar Rass	Al Awamiyah	Dhurma
Asia	Bisha	Shaqra	Al Ais
Australia	Tārūt Island	As Sulayyil	Al Hayathem
Africa	Saihat	Nairyah	Al Ju'ranah
America	Sharurah	Howtat Bani Tamim	Al-Ahsa
Russia	Bahrah	Turbah	Hillat Muhaish
Europe	Khafji	Haql	Al Jafr
Saudi Arabia	Sabya	Al-Jumum	Huraymila
Riyadh	Al Duwadimi	Duba	Tumair
Jeddah	Abu Arish	Ahad Al Masarihah	Al Rumailah
Mecca	Zulfi	Al Qunfudhah	Ad Darb
Al-Madinah Al-Munawwarah	Ahad Rafidah	Damad	Alhada
Dammam	Rabigh	Dhahran Al Janub	Al Badi'
Al Hafuf-Al Mubarraz	Ras Tanura	Al Tarf	Alaliya
Taif	Rafha	AlQouz	Al Khadra'
Tabuk	Safwa	Anak	Algorn
Buraydah	Tubarjal	Al Qaisumah	Al Khuwaildiyah
Khamis Mushait	Turaif	Al Quwaiiyah	Almuzaylif
Al Jubail	Al Majma'ah	Al Makhwah	Al Hariq
Aseer Province	Al Badayea	Ranyah	At Tawbi
Hail	Al Qassim Province	Rumah	Tathleeth
Najran	Afif	Sabt Al Alayah	Al-Itayn
Hafar al-Batin	Baljurashi	Hautat Sudair	Al Edabi
Abha	Diriyah	Al Lith	Al-Matan
Al-Thuqbah	Ad-Dilam	Al Munayzilah	Thadiq
Yanbu	Umluj	Umran	Al-Badie Al-Shamali
Delhi	Guatemala	Kazakhstan	Mozambique
Comoros	Guyana	La Russe	Namiba
Afghanistan	Hong Kong	Macedonia	Nigeria
Pakistan	Honduras	Sri Lanka	Uganda
Azerbaijan	Croatia	Liberia	Norway
Belarus	Haiti	Libya	Nepal
Belize	Hungary	Morocco	Zimbabwe
Democratic Republic of the Congo	Indonesia	Vietnam	South Africa
Switzerland	Israel	Sweden	Philippines
Chile	Isle of Man	Singapore	Pakistan
Colombia	Iceland	Somalia	Poland
Costa Rica	United Kingdom	Suriname	Uzbekistan
Cuba	Jamaica	Salvador	Romania
Islands of Cape Verde	Baban	Syria	Russia
Czechoslovakia	Kenya	Thailand	Serbia
Djibouti	Solomon Islands	Mongolia	Mexico
Dominica	North Korea	Tanzania	Dahaban
Denmark	Cambodia	Tunisia	Malaysia

Table B.4(b-1) Geographies English Stop Words			
Algeria	South Korea	Maldives	Al Hait
Estonia	Cayman Islands	Ukraine	Al Markaz
Al-Khobar	Buqayq	Eastern Province	Beirut
Riyadh Al Khabra	El-Ayoun	Arar	Masliyah
Unaizah	Dumat al-Jandal	Al Haeer	Ayn Ibn Fuhayd
Sakākā	Samtah	Al Henakiyah	Ar Ruwaidhah
Al-Jawf Province	AlUla	Khaybar	Almutayrifi
Al Hawiyah	Layla	Al Aqiq	Bahr Abu Sukaynah
Jizan	Baish	Tanomah	Bir Ibn Hirmas
Dhahran	Al Wajh	Al Uwayqilah	Mulayjah
Al Mithnab	Tayma	Farasan	Japan
Al Bukayriyah	Al-Muzahmiya	Baqaa	Tokyo
Canada	Britain	Gambia	Umm As Sahik
Muscat	Bahrain	London	New Guinea
Ash Shimasiyah	Kuwait	China	Khartoum
Al Dulaymiyah	Amman	Beijing	Baghdad
Al Yamama	Emirates	India	Al Aridhah
Tabalah	Qatar	Eritrea	Abu Dhabi
Al Khadra	Iraq	Ethiopia	Ad-Dawhah
Al-Fuwayliq	Jordan	Spain	Sana'a
Rawdat Habbas	Yemen	Venezuela	Cairo
Al Quwarah	Egypt	Falkland	Washington
Ad Dubaiyah	Sudan	Ronda	Germany
Al Sudayrah	Lebanon	Georgia	Berlin
Naajan	Iran	Jersey	France
Al Laqiya	Turkey	Ghana	Paris
Dhalm	Manama	Gibraltar	Moscow
Ath Thybiyah	Oman		

Table B.4(b-2) Number and Dates English Stop Words				
HUNDRED	Ramadan	Twenty-six	Sixty-two	Ninety-nine
THOUSAND	Shawwal	Twenty-seven	Sixty-three	One hundred
MILLION	Dhul Qadah	Twenty-eight	Sixty-four	I
BILLION	Dhul Hijjah	Twenty-nine	Sixty-five	II
TRILLION	Monday	Thirty	Sixty-six	III
ANNUAL	Tuesday	Thirty-one	Sixty-seven	IV
ANNUALLY	Wednesday	Thirty-two	Sixty-eight	V
ANNUM	Thursday	Thirty-three	Sixty-nine	VI
YEAR	Friday	Thirty-four	Seventy	VII
YEARLY	Sunday	Thirty-five	Seventy-one	VIII
QUARTER	Saturday	Thirty-six	Seventy-two	IX
QUARTERLY	One	Thirty-seven	Seventy-three	X
MONTH	Two	Thirty-eight	Seventy-four	XI
MONTHLY	Three	Thirty-nine	Seventy-five	XII
WEEK	Four	Forty	Seventy-six	XIII
WEEKLY	Five	Forty-one	Seventy-seven	XIV
JANUARY	Six	Forty-two	Seventy-eight	XV
FEBRUARY	Seven	Forty-three	Seventy-nine	XVI
MARCH	Eight	Forty-four	Eighty	XVII
APRIL	Nine	Forty-five	Eighty-one	XVIII
MAY	Ten	Forty-six	Eighty-two	XIX
JUNE	Eleven	Forty-seven	Eighty-three	XX
JULY	Twelve	Forty-eight	Eighty-four	XXI
AUGUST	Thirteen	Forty-nine	Eighty-five	XXII
SEPTEMBER	Fourteen	Fifty	Eighty-six	XXIII
OCTOBER	Fifteen	Fifty-one	Eighty-seven	XXIV
NOVEMBER	Sixteen	Fifty-two	Eighty-eight	XXX
DECEMBER	Seventeen	Fifty-three	Eighty-nine	XL
Muharram	Eighteen	Fifty-four	Ninety	L
Safar	Nineteen	Fifty-five	Ninety-one	LX
Rabi al-awwal	Twenty	Fifty-six	Ninety-two	LXX
Rabi al-thani	Twenty-one	Fifty-seven	Ninety-three	LXXX
Jumada al-awwal	Twenty-two	Fifty-eight	Ninety-four	XC
Jumada al-thani	Twenty-three	Fifty-nine	Ninety-six	C
Rajab	Twenty-four	Sixty	Ninety-seven	CI
Sha'aban	Twenty-five	Sixty-one	Ninety-eight	CII
CC	DC	M	MMI	MI
CCC	DCC	MMM	MMII	MII
CD	DCCC	MCM	MMMM	MIII
D	CM	MM	V	MMC

Table B.4(b-3) English Company Long Name Stop Words	
Methanol Chemicals Company	National Shipping Company of Saudi Arabia
Saudi Basic Industries Corp.	Riyad Bank
SABIC Agri-Nutrients Co.	Bank Aljazira
National Industrialization Co.	Saudi Investment Bank
Alujain Corp	Banque Saudi Fransi
Nama Chemicals Co.	Arab National Bank
Saudi Industrial Investment Group	Al Rajhi Bank
Yanbu National Petrochemical Co.	Bank Albilad
Sahara International Petrochemical Co.	Alinma Bank
Advanced Petrochemical Co.	The Saudi National Bank
Saudi Kayan Petrochemical Company	Amlak International for Real Estate Finance Co.
Hail Cement Co.	Saudi British Bank
Najran Cement Company	Riyad REIT Fund
City Cement Co.	Musharaka REIT Fund
Northern Region Cement Co.	Jadwa REIT Saudi Fund
Umm Al-Qura Cement Company	MEFIC REIT Fund
Arabian Cement Co.	SEDCO CAPITAL REIT Fund
Yamama Cement Company	AL Maather REIT Fund
Saudi Cement Company	AlAhli REIT Fund 1
Southern Province Cement Co.	Derayah REIT Fund
Yanbu Cement Co.	Bonyan REIT Fund
Eastern Province Cement Co.	Jadwa REIT Al Haramain Fund
Tabuk Cement Co.	Al Rajhi REIT Fund
Al Jouf Cement Company	Alkhabeer REIT Fund
Al Kathiri Holding Co.	AlJazira REIT
Takween Advanced Industries Co.	Arabian Contracting Services Co.
Basic Chemical Industries Co.	Tihama Advertising and Public Relations Co.
Saudi Arabian Mining Company	Saudi Research and Media Group
Zahrat Al Waha for Trading Co.	Red Sea International Company
Middle East Paper Co.	Saudi Real Estate Co.
The National Company For Glass Industries	Alandalus Property Co.
Filing and Packing Materials Manufacturing Co.	Arabian Centres Co.
National Metal Manufacturing and Casting Co.	Taiba Investments Co.
Saudi Paper Manufacturing Co.	Makkah Construction and Development Co.
United Wire Factories Company	Arriyadh Development Co.
Saudi Steel Pipe Co.	Emaar The Economic City
National Gypsum Company	Jabal Omar Development Company
Arabian Pipes Company	Dar Alarkan Real Estate Development Co
Zamil Industrial Investment Co.	Knowledge Economic City
Rabigh Refining and Petrochemical Company	Saudi Industrial Services Co.
Aldrees Petroleum and Transport Services Co.	Theeb Rent a Car Company
National Gas and Industrialization Co.	Saudi Ground Services Co.
Saudi Arabian Oil Company	Saudi Public Transport Co.
Batic Investments and Logistics Co.	Jarir Marketing Co.
United International Transportation Co.	Fawaz Abdulaziz Alhokair Co.

Table B.4(b-3) English Company Long Name Stop Words	
Arabian Internet and Communications Services Co.	Saudi Company for Hardware
Elm Co.	Al Hassan Ghazi Ibrahim Shaker Co.
Al Moammar Information Systems Company	Al-Omran Industries & Trading Co.
Arab Sea Information Systems Co.	Astra Industrial Group
Etihad Etisalat Co.	Saudi Industrial Export Co.
Mobile Telecommunication Company Saudi Arabia	Bawan Company
Etihad Atheeb Telecommunication Company	Electrical Industries Company
Saudi Telecom Co.	Saudi Ceramic Co.
Saudi Airlines Catering Company	Saudi Cable Co.
Maharah Human Resources Company	Saudi Arabian Amiantit Co.
Saudi Printing and Packaging Company	Al-Babtain Power and Telecommunication Co.
Sadr Logistics Co.	Saudi Vitrified Clay Pipes Co.
Savola Group	Middle East Specialized Cables Co.
Wafrah for Industry & Development Co.	Leejam Sports Co.
Saudia Dairy and Foodstuff Co.	Raydan Food Co.
Tanmiah Food Company	Alkhaleej Training and Education Co.
Almarai Company	Herfy Food Services Co.
Halwani Bros. Co.	Seera Group Holding
National Agricultural Development Co.	Abdulmohsen Alhokair Group for Tourism and Development
Al Gassim Investment Holding Co.	Tourism Enterprise Co.
Tabuk Agricultural Development Co.	Dur Hospitality Company
Saudi Fisheries Co.	Lazurde Company for Jewelry
Ash-Sharqiyah Development Co.	Thob Al Aseel Co.
Al-Jouf Agricultural Development Co.	Fitaihi Holding Group
Jazan Energy and Development Co.	Naseej International Trading Co.
ACWA Power Company	Al Abdullatif Industrial Investment Co.
Alkhorayef Water and Power Technologies Co.	Alinma Tokio Marine Co.
Saudi Electricity Co.	Al-Rajhi Company for Cooperative Insurance
BinDawood Holding Co	Saudi Enaya Cooperative insurance Company
Nahdi Medical Co	CHUBB Arabia Cooperative Insurance Co.
Abdullah Al Othaim Markets Company	Al Sagr Cooperative Insurance Co
Saudi Marketing Co	Bupa Arabia for Cooperative Insurance Co.
Thimar Development Holding Co	United Cooperative Assurance Co.
Anaam International Holding Group	Saudi Reinsurance Co.
Abdullah Saad Mohammed Abo Moati for Bookstores Co.	Al Alamiya for Cooperative Insurance Co.
Baazeem Trading Company	Buruj Cooperative Insurance Co.
United Electronics Co.	Gulf General Cooperative Insurance Co.
Saudi Automotive Services Co.	Gulf Insurance Group
Allied Cooperative Insurance Group	Amana Cooperative Insurance Co.
Gulf Union Alahlia Cooperative Insurance Co.	Wataniya Insurance Company
Saudi Arabian Cooperative Insurance Company	Al-Etihad Cooperative Insurance Co.
Arabian Shield Cooperative Insurance Company	Arabia Insurance Cooperative Company

Table B.4(b-3) English Company Long Name Stop Words	
Allianz Saudi Fransi Cooperative Insurance Company	Dallah Healthcare Company
The Company for Cooperative Insurance	National Medical Care Co.
Aljazira Takaful Taawuni Company	AYYAN Investment Co.
Malath Cooperative Insurance Company	Saudi Chemical Co.
The Mediterranean and Gulf Insurance and Reinsurance Co.	Scientific and Medical Equipment House Co.
Middle East Healthcare Co.	Saudi Pharmaceutical Industries and Medical Appliances Corp
Dr. Sulaiman Al Habib Medical Services Group	Saudi Advanced Industries Co.
Mouwasat Medical Services Co	Sinad Holding Co.
Al Hammadi Holding	Nayifat Finance Company
Retal Urban Development Co	Al-Baha Investment and Development Co.
Americana Restaurants International PLC Co	Kingdom Holding Company
Saudi Industrial Development Co	Aldawaa Medical Services Co.
Saudi Tadawul Group Holding Co	Saudi Home Loans
Taleem REIT Fund	Al Masane Al Kobra Mining Co
SICO Saudi REIT Fund	

Table B.4(b-4) English Company Short Name Stop Words			
Chemanol	Alinma	TANMIAH	ALRAJHI TAKAFUL
SABIC	SNB	Almarai	Enaya
SABIC AGRI-NUTRIENTS	Amlak	HB	CHUBB
TASNEE	SABB	NADEC	ALSAGR INSURANCE
ALUJAIN	RIYAD REIT	GACO	BUPA ARABIA
Nama Chemicals	MUSHARAKA REIT	TADCO	UCA
SIIG	Jadwa REIT Saudi	SFICO	Saudi Re
YANSAB	MEFIC REIT	SHARQIYAH DEV	ALALAMIYA
Sipchem	SEDCO CAPITAL REIT	ALJOUF	BURUJ
Advanced	AL Maather REIT	JAZADCO	Gulf General
Saudi Kayan	AlAhli REIT	ACWA Power	GIG
HCC	DERAYAH REIT	AWPT	Amana Insurance
Najran Cement	Bonyan REIT	SAUDI ELECTRICITY	Wataniya
City Cement	JADWA REIT ALHARAMAIN	BINDAWOOD	ALETIHAD
UACC	ALKHABEER REIT	A.Othaim Market	ACIG
NORTHERN CEMENT	Al Rajhi REIT	NAHDI	AICC
ACC	ALJAZIRA REIT	FARM SUPERSTORES	Gulf Union Alahlia
YSCC	ALARABIA	THIMAR	SAICO

Table B.4(b-4) English Company Short Name Stop Words			
Saudi Cement	TAPRCO	ANAAM HOLDING	Arabian Shield
SPCC	SRMG	ABO MOATI	Walaa
YCC	Red Sea	Baazeem	Salama
EPCCO	SRECO	Extra	Allianz SF
TCC	ALANDALUS	SASCO	Tawuniya
Jouf Cement	CENOMI CENTERS	JARIR	Jazira Takaful
ALKATHIRI	Taiba	CENOMI RETAIL	Malath Insurance
TAKWEEN	MCDC	SACO	MEDGULF
BCI	ARDCO	SHAKER	SAUDI GERMAN HEALTH
MAADEN	Emaar EC	ALOMRAN	SULAIMAN ALHABIB
OASIS	Jabal Omar	ASTRA INDUSTRIAL	MOUWASAT
MEPCO	DAR ALARKAN	SIECO	ALHAMMADI
ZOUJAJ	KEC	Bawan	Dallah Health
FIPCO	SISCO	EIC	Care
Maadaniyah	Theeb	Saudi Ceramics	AYYAN
ALDREES	Arab Sea	ALKHALEEJ TRNG	Kingdom
GASCO	Etihad Etisalat	Herfy Foods	ALDAWAA
SPM	SGS	SAUDI CABLE	CHEMICAL
ASLAK	SAPTCO	Amiantit	EQUIPMENT HOUSE
SSP	BATIC	ALBABTAIN	SPIMACO
NGC	Budget Saudi	SVCP	SAIC
APC	SOLUTIONS	MESC	SINAD HOLDING
ZAMIL INDUST	ELM	FITNESS TIME	Nayifat
Petro Rabigh	MIS	RAYDAN	ALBAHA
Saudi Aramco	ZAIN KSA	SEERA	SHL
BAHRI	Atheeb Telecom	ALHOKAIR GROUP	AMAK
RIBL	STC	TECO	SICO SAUDI REIT
BJAZ	Catering	Dur	TALEEM REIT
SAIB	Maharah	LAZURDE	Retal
BSFR	SPPC	ALASEEL	Americana Restaurants
ANB	Sadr	Fitaihi Group	SIDC
ALRAJHI	Savola Group	Naseej	TADAWUL GROUP
ALBILAD	Wafrah	ALABDULLATIF	ALINMA RETAIL REIT
MULKIA REIT	SADAFCO	Alinma Tokio M	

Chapter 5 - Appendix C

Appendix C.1 - Arabic Annual Reports

Table C.1 (a-1) Most Frequent Positive Sentiment Words Occurring in the Arabic Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	تَحْقِيق	16,828	5.86	5.86	26	اِسْتِفادَة	2,677	0.93	60.33
2	تَطْوِير	15,819	5.51	11.36	27	تَمْكِين	2,581	0.90	61.23
3	نُمُوّ	11,890	4.14	15.50	28	رِبْحِيّ	2,494	0.87	62.09
4	تَعْزِيز	11,499	4.00	19.51	29	مُتَمَيِّز	2,320	0.81	62.90
5	دَعْم	9,777	3.40	22.91	30	عَزَّز	2,280	0.79	63.69
6	قُدْرَة	9,434	3.28	26.19	31	ثِقَة	2,269	0.79	64.48
7	تَحْسِين	8,875	3.09	29.28	32	أَتاح	2,218	0.77	65.26
8	ضَمان	8,431	2.93	32.22	33	إِيجابِيّ	2,158	0.75	66.01
9	كَفاءَة	7,015	2.44	34.66	34	تَجاوَز	2,067	0.72	66.73
10	أَعْلَى	6,627	2.31	36.97	35	أَكَّد	2,045	0.71	67.44
11	أَفْضَل	6,193	2.16	39.12	36	شَفّافِيَّة	1,960	0.68	68.12
12	حَلّ	5,748	2.00	41.12	37	تَطَوُّر	1,908	0.66	68.79
13	فُرْصَة	5,517	1.92	43.04	38	قِيادَة	1,854	0.65	69.43
14	فَعّالِيَّة	5,006	1.74	44.78	39	رَغْم مِن	1,800	0.63	70.06
15	حَقَّق	4,975	1.73	46.52	40	أَقْصَى	1,664	0.58	70.64
16	قُوَّة	4,525	1.58	48.09	41	جائِزَة	1,653	0.58	71.21
17	نَجاح	4,371	1.52	49.61	42	تَأْكِيد	1,647	0.57	71.79
18	تَقَدَّم	4,329	1.51	51.12	43	تَمَيُّز	1,632	0.57	72.35
19	رائِد	4,031	1.40	52.52	44	نَجَح	1,610	0.56	72.91
20	تَعاوُن	3,994	1.39	53.91	45	ضَمِن	1,544	0.54	73.45
21	إِنْجاز	3,782	1.32	55.23	46	تَمَتَّع	1,514	0.53	73.98
22	قَوِيّ	3,188	1.11	56.34	47	مُسْتَهْدَف	1,443	0.50	74.48
23	فَعّال	3,035	1.06	57.40	48	مُرُونَة	1,417	0.49	74.97
24	اِبْتِكار	2,902	1.01	58.41	49	تَقَدُّم	1,354	0.47	75.44
25	مَزِيَّة	2,842	0.99	59.40	50	مُنْتَظِم	1,317	0.46	75.90
All							282,927		

This table presents the most frequent positive sentiment words in Arabic annual reports. The occurrences of the Arabic words were identified using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Arabic words Frequencies and cumulative percentages reflect lemma/token-level matches.

Table C.1 (b-1) Most Frequent Negative Sentiment Words Occurring in the Arabic Annual Reports

Rank					Rank				
	Word	Total	%	Cum %		Word	Total	%	Cum %
1	خَسارَة	7,431	5.86	5.86	26	ٱِنْخَفَض	937	0.74	40.12
2	ٱِنْخِفاض	5,079	4.01	9.87	27	مُشْكِلَة	903	0.71	40.83
3	تَحَدِّي	3,407	2.69	12.55	28	ٱِعْتِراف	901	0.71	41.54
4	تَعْوِيض	2,904	2.29	14.84	29	مُخالَفَة	860	0.68	42.22
5	تَقْلِيل	2,744	2.16	17.01	30	مُطالَبَة	850	0.67	42.89
6	خَضَع	2,037	1.61	18.62	31	تَحَمَّل	846	0.67	43.56
7	سَلْبِيّ	1,983	1.56	20.18	32	صُعُوبَة	844	0.67	44.23
8	تَخْفِيض	1,686	1.33	21.51	33	أَدان	841	0.66	44.89
9	عارَض	1,655	1.31	22.81	34	خَطَأ	826	0.65	45.54
10	مُواجَهَة	1,545	1.22	24.03	35	إِنْهاء	799	0.63	46.17
11	تَنازُل	1,544	1.22	25.25	36	ٱِسْتِغْلال	792	0.62	46.79
12	ضُعْف	1,498	1.18	26.43	37	عَدَم قُدْرَة	758	0.60	47.39
13	تَخْفِيف	1,493	1.18	27.61	38	فَرَض	744	0.59	47.98
14	بالِغ	1,474	1.16	28.77	39	حَرَم	739	0.58	48.56
15	خَفْض	1,415	1.12	29.89	40	ضَرُورِيّ	730	0.58	49.14
16	حادِث	1,394	1.10	30.99	41	خِلاف	722	0.57	49.71
17	حَمَل	1,388	1.09	32.08	42	مَنْع	721	0.57	50.28
18	تَسْوِيَة	1,363	1.08	33.16	43	ٱِسْتِبْدال	721	0.57	50.84
19	أَزْمَة	1,340	1.06	34.21	44	فَصْل	713	0.56	51.41
20	ٱِسْتِفْسار	1,260	0.99	35.21	45	إِغْلاق	709	0.56	51.97
21	إِلْغاء	1,160	0.91	36.12	46	ٱِحْتِيال	672	0.53	52.50
22	ضِدّ	1,147	0.90	37.03	47	إِعادَة هَيْكَلَة	667	0.53	53.02
23	غَطَّى	1,095	0.86	37.89	48	أَثار	665	0.52	53.55
24	عُقُوبَة	953	0.75	38.64	49	مَوْقِف	664	0.52	54.07
25	ضَرَر	937	0.74	39.38	50	تَراجُع	658	0.52	54.59
All							139,645		

This table presents the most frequent negative sentiment words in Arabic annual reports. The occurrences of the Arabic words were identified using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Arabic words Frequencies and cumulative percentages reflect lemma/token-level matches.

Table C.1 (c-1) Most Frequent Uncertain Sentiment Words Occurring in the Arabic Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	مَخاطِر	44,938	51.97	51.97	26	راجَع	376	0.43	92.45
2	مُتَوَقَّع	4,586	5.30	57.28	27	تَراوَح	338	0.39	92.84
3	مُقْتَرَح	2,995	3.46	60.74	28	مُرَجِّح	298	0.34	93.18
4	تَعَرَّض	2,684	3.10	63.84	29	وِقايَة	292	0.34	93.52
5	مُحْتَمَل	2,677	3.10	66.94	30	اِقْتَرَح	289	0.33	93.85
6	تَوَقَّع	2,662	3.08	70.02	31	تَنَبُّؤ	287	0.33	94.19
7	قَدَّر	2,353	2.72	72.74	32	مِن مُحْتَمَل	265	0.31	94.49
8	مُتَغَيِّر	1,749	2.02	74.76	33	غَيْر مَلْمُوس	264	0.31	94.80
9	مَعْقُول	1,579	1.83	76.59	34	مُخاطَرَة	264	0.31	95.10
10	إِيضاح	1,406	1.63	78.21	35	مُتَفاوِت	241	0.28	95.38
11	إِمْكانِيَّة	1,403	1.62	79.84	36	مُمْكِن أَنَّ	213	0.25	95.63
12	تَوَقَّع	1,373	1.59	81.43	37	عَدَم يَقِين	211	0.24	95.87
13	أَظْهَر	1,336	1.55	82.97	38	تَغَيَّر	199	0.23	96.10
14	حِوال	1,023	1.18	84.15	39	مُتَحَفِّظ	188	0.22	96.32
15	اِفْتِراض	984	1.14	85.29	40	رُبَّما	167	0.19	96.51
16	اِحْتِمال	974	1.13	86.42	41	مُعْتاد	158	0.18	96.70
17	تَحَفُّظ	706	0.82	87.23	42	مُعْتَمَد عَلَى	151	0.17	96.87
18	اِعْتَقَد	661	0.76	88.00	43	ما قَرُب	147	0.17	97.04
19	تَقْرِيب	615	0.71	88.71	44	بَدا	115	0.13	97.17
20	تَوْضِيح	604	0.70	89.41	45	نادِر	114	0.13	97.31
21	قارَب	555	0.64	90.05	46	مَشْرُوط	113	0.13	97.44
22	مُؤَقَّت	455	0.53	90.58	47	مِن مُرَجِّح	110	0.13	97.56
23	مَبْدَئِيّ	435	0.50	91.08	48	مِن حِين آخَر	98	0.11	97.68
24	اِفْتِراضِيّ	403	0.47	91.55	49	إِعادَة نَظَر	95	0.11	97.79
25	تَعْلِيق	403	0.47	92.01	50	اِسْتِباق	87	0.10	97.89
All							104,580		

This table presents the most frequent uncertain sentiment words in Arabic annual reports. The occurrences of the Arabic words were identified using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Arabic words Frequencies and cumulative percentages reflect lemma/token-level matches.

Appendix C.2 - English Annual Reports

Table C.2 (a-1) Most Frequent Positive Sentiment Words Occurring in the English Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	achieve	5,493	4.68	4.68	26	innovative	1,666	1.42	58.28
2	best	5,004	4.26	8.93	27	improvement	1,641	1.40	59.68
3	efficiency	4,216	3.59	12.52	28	successfully	1,268	1.08	60.76
4	opportunities	3,920	3.34	15.86	29	successful	1,266	1.08	61.84
5	enhance	3,403	2.90	18.76	30	better	1,250	1.06	62.90
6	strong	3,274	2.79	21.54	31	improved	1,194	1.02	63.92
7	achieving	3,122	2.66	24.20	32	good	1,165	0.99	64.91
8	improve	3,108	2.65	26.85	33	satisfaction	1,084	0.92	65.83
9	leading	3,008	2.56	29.41	34	efficient	1,070	0.91	66.74
10	achieved	2,874	2.45	31.85	35	strengthen	1,052	0.90	67.64
11	success	2,770	2.36	34.21	36	opportunity	982	0.84	68.47
12	leadership	2,483	2.11	36.32	37	strengths	934	0.79	69.27
13	highest	2,216	1.89	38.21	38	enhanced	923	0.79	70.05
14	innovation	2,170	1.85	40.06	39	enabling	888	0.76	70.81
15	improving	2,062	1.76	41.81	40	collaboration	855	0.73	71.54
16	enhancing	1,980	1.69	43.50	41	achievement	829	0.71	72.24
17	positive	1,916	1.63	45.13	42	pleased	788	0.67	72.91
18	profitability	1,822	1.55	46.68	43	strengthening	778	0.66	73.58
19	integrity	1,759	1.50	48.17	44	strength	771	0.66	74.23
20	progress	1,753	1.49	49.67	45	exceptional	769	0.65	74.89
21	excellence	1,727	1.47	51.14	46	gain	700	0.60	75.48
22	enable	1,694	1.44	52.58	47	enables	690	0.59	76.07
23	achievements	1,693	1.44	54.02	48	advantage	661	0.56	76.63
24	despite	1,675	1.43	55.45	49	improvements	623	0.53	77.16
25	transparency	1,668	1.42	56.86	50	reward	613	0.52	77.68
All							117,137		

This table presents the most frequent positive sentiment words in English annual reports. The occurrences of the English words were identified using Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Table C.2 (b-1) Most Frequent Negative Sentiment Words Occurring in the English Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	loss	4,145	5.22	5.22	26	adversely	597	0.75	40.53
2	losses	2,835	3.57	8.80	27	challenging	584	0.74	41.27
3	against	2,550	3.21	12.01	28	violations	531	0.67	41.93
4	challenges	2,447	3.08	15.09	29	cancellation	518	0.65	42.59
5	claims	1,890	2.38	17.48	30	disclose	493	0.62	43.21
6	conflict	1,499	1.89	19.36	31	restructuring	477	0.60	43.81
7	impairment	1,485	1.87	21.24	32	conflicts	437	0.55	44.36
8	exposed	1,469	1.85	23.09	33	concerns	408	0.51	44.87
9	negative	1,123	1.42	24.50	34	difficulties	408	0.51	45.39
10	weaknesses	975	1.23	25.73	35	penalty	394	0.50	45.89
11	negatively	930	1.17	26.90	36	challenge	392	0.49	46.38
12	adverse	891	1.12	28.03	37	questions	385	0.49	46.86
13	disclosed	864	1.09	29.11	38	incidents	382	0.48	47.35
14	failure	857	1.08	30.19	39	complaints	372	0.47	47.81
15	concerned	811	1.02	31.22	40	stress	371	0.47	48.28
16	fraud	775	0.98	32.19	41	lack	364	0.46	48.74
17	damage	731	0.92	33.11	42	errors	362	0.46	49.20
18	inability	730	0.92	34.03	43	overcome	361	0.45	49.65
19	decline	708	0.89	34.93	44	solvency	359	0.45	50.10
20	crisis	701	0.88	35.81	45	unable	356	0.45	50.55
21	concern	652	0.82	36.63	46	disruption	350	0.44	50.99
22	penalties	646	0.81	37.45	47	laundering	346	0.44	51.43
23	absence	625	0.79	38.23	48	termination	339	0.43	51.86
24	default	625	0.79	39.02	49	difficult	337	0.42	52.28
25	dismissal	600	0.76	39.78	50	objection	332	0.42	52.70
All							80,869		

This table presents the most frequent negative sentiment words in English annual reports. The occurrences of the English words were identified using Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Table C.2 (c-1) Most Frequent Uncertain Sentiment Words Occurring in the English Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	risk	27,995	33.66	33.66	26	fluctuation	248	0.30	90.94
2	risks	17,901	21.52	55.18	27	depending	243	0.29	91.23
3	may	13,655	16.42	71.60	28	vary	238	0.29	91.52
4	could	2,015	2.42	74.02	29	nearly	219	0.26	91.78
5	possible	1,887	2.27	76.29	30	contingent	218	0.26	92.04
6	exposure	1,807	2.17	78.46	31	clarification	214	0.26	92.30
7	approximately	926	1.11	79.57	32	almost	213	0.26	92.55
8	believes	918	1.10	80.68	33	dependent	203	0.24	92.80
9	precautionary	867	1.04	81.72	34	assuming	198	0.24	93.04
10	fluctuations	851	1.02	82.74	35	suggesting	188	0.23	93.26
11	assumptions	768	0.92	83.66	36	unusual	183	0.22	93.48
12	depends	687	0.83	84.49	37	probable	181	0.22	93.70
13	variable	573	0.69	85.18	38	assumed	180	0.22	93.92
14	believe	552	0.66	85.84	39	uncertainties	170	0.20	94.12
15	might	486	0.58	86.43	40	probability	170	0.20	94.33
16	possibility	454	0.55	86.97	41	differ	166	0.20	94.52
17	uncertainty	447	0.54	87.51	42	predict	161	0.19	94.72
18	exposures	422	0.51	88.02	43	precautions	159	0.19	94.91
19	variables	367	0.44	88.46	44	varying	151	0.18	95.09
20	revised	352	0.42	88.88	45	assume	148	0.18	95.27
21	preliminary	341	0.41	89.29	46	likelihood	145	0.17	95.44
22	fluctuate	301	0.36	89.65	47	assumes	139	0.17	95.61
23	intangible	285	0.34	90.00	48	anticipate	133	0.16	95.77
24	depend	282	0.34	90.34	49	suggest	133	0.16	95.93
25	anticipated	252	0.30	90.64	50	clarifications	129	0.16	96.09
All							86,033		

This table presents the most frequent uncertain sentiment words in English annual reports. The occurrences of the English words were identified using Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Appendix C.3 - Arabic CEO Letters

Table C.3 (a-1) Most Frequent Positive Sentiment Words Occurring in the Arabic CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	نُمُوّ	1,132	6.67	6.67	26	جائِزَة	167	0.98	61.86
2	تَحْقِيق	1,094	6.44	13.11	27	ضَمان	159	0.94	62.80
3	تَعْزِيز	761	4.48	17.59	28	إِيجابِيّ	157	0.92	63.73
4	تَطْوِير	725	4.27	21.86	29	تَعاوُن	153	0.90	64.63
5	دَعْم	613	3.61	25.47	30	ٱِسْتِثْنائِيّ	148	0.87	65.50
6	نَجاح	493	2.90	28.38	31	تَقَدُّم	147	0.87	66.36
7	حَقَّق	485	2.86	31.23	32	قِيادَة	139	0.82	67.18
8	تَحْسِين	398	2.34	33.58	33	تَمَيُّز	137	0.81	67.99
9	إِنْجاز	384	2.26	35.84	34	نَجَح	136	0.80	68.79
10	فُرْصَة	384	2.26	38.10	35	تَمْكِين	134	0.79	69.58
11	قُدْرَة	370	2.18	40.28	36	رَغْم مِن	127	0.75	70.33
12	أَفْضَل	366	2.16	42.43	37	مُرُونَة	125	0.74	71.06
13	كَفاءَة	323	1.90	44.34	38	تَطَوُّر	125	0.74	71.80
14	قُوَّة	299	1.76	46.10	39	رِبْحِيّ	122	0.72	72.52
15	حَلّ	275	1.62	47.72	40	أَكَّد	102	0.60	73.12
16	رائِد	273	1.61	49.33	41	عَلَى رَغْم	92	0.54	73.66
17	ٱِبْتِكار	254	1.50	50.82	42	مُسْتَهْدَف	90	0.53	74.19
18	مُتَمَيِّز	253	1.49	52.31	43	ناجِح	88	0.52	74.71
19	قَوِيّ	245	1.44	53.75	44	تَجاوَز	86	0.51	75.22
20	ثِقَة	235	1.38	55.14	45	أَتاح	84	0.49	75.71
21	أَعْلَى	222	1.31	56.45	46	تَحَسُّن	83	0.49	76.20
22	ٱِسْتِفادَة	202	1.19	57.64	47	مُتَقَدِّم	83	0.49	76.69
23	تَقَدَّم	199	1.17	58.81	48	رَغْم	78	0.46	77.15
24	وَلاء	179	1.05	59.86	49	مُمَيَّز	77	0.45	77.60
25	عَزَّز	173	1.02	60.88	50	راسِخ	74	0.44	78.04
All							16,882		

This table presents the most frequent positive sentiment words in Arabic CEO letters. The occurrences of the Arabic words were identified using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Arabic words Frequencies and cumulative percentages reflect lemma/token-level matches.

Table C.3 (b-1) Most Frequent Negative Sentiment Words Occurring in the Arabic CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	تَحَدِّي	343	13.10	13.10	26	حادِث	22	0.84	56.26
2	خَسارَة	103	3.93	17.04	27	مُؤَخَّر	21	0.80	57.07
3	اِنْخِفاض	95	3.63	20.66	28	عَقَبَة	21	0.80	57.87
4	خَفْض	75	2.86	23.53	29	مُعارِض	20	0.76	58.63
5	مُواجَهَة	74	2.83	26.36	30	جادّ	20	0.76	59.40
6	تَقْلِيل	63	2.41	28.76	31	غالِي	20	0.76	60.16
7	صَعْب	55	2.10	30.86	32	تَخارُج	19	0.73	60.89
8	تَداعِي	51	1.95	32.81	33	غَطّى	19	0.73	61.61
9	بالِغ	49	1.87	34.68	34	حادّ	18	0.69	62.30
10	أَزْمَة	46	1.76	36.44	35	فات	18	0.69	62.99
11	حَرَم	43	1.64	38.08	36	تَفَشِّي	18	0.69	63.67
12	إِغْلاق	42	1.60	39.69	37	حَجْز	17	0.65	64.32
13	إِعادَة هَيْكَلَة	42	1.60	41.29	38	مُنافِس	17	0.65	64.97
14	تَخْفِيف	40	1.53	42.82	39	اِحْتاج	17	0.65	65.62
15	حَمَل	36	1.38	44.19	40	ضِدّ	17	0.65	66.27
16	لَوْم	34	1.30	45.49	41	إِصابَة	17	0.65	66.92
17	اِنْخَفَض	34	1.30	46.79	42	آل	16	0.61	67.53
18	تَرْشِيد	30	1.15	47.94	43	حَظْر	15	0.57	68.11
19	سَلْبِيّ	30	1.15	49.08	44	ضُعْف	14	0.53	68.64
20	فَرَض	29	1.11	50.19	45	تَعْوِيض	13	0.50	69.14
21	صُعُوبَة	29	1.11	51.30	46	ضَرُورِيّ	13	0.50	69.63
22	تَخْفِيض	29	1.11	52.41	47	اِكْتَشَف	13	0.50	70.13
23	مِحْوَرِيّ	29	1.11	53.51	48	مَعْرِض	12	0.46	70.59
24	اِسْتِغْلال	25	0.95	54.47	49	عانَى	12	0.46	71.05
25	تَراجُع	25	0.95	55.42	50	قَطَع	12	0.46	71.50
All							2,746		

This table presents the most frequent negative sentiment words in Arabic CEO letters. The occurrences of the Arabic words were identified using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Arabic words Frequencies and cumulative percentages reflect lemma/token-level matches.

Table C.3 (c-1) Most Frequent Uncertain Sentiment Words Occurring in the Arabic CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	مَخاطِر	110	11.92	11.92	26	لَعَلَّ	7	0.76	87.97
2	قَدَّر	77	8.34	20.26	27	تَعْلِيق	7	0.76	88.73
3	تَوَقُّع	74	8.02	28.28	28	اِنْتَظَر	7	0.76	89.49
4	مُتَوَقَّع	71	7.69	35.97	29	مُقْتَرَح	6	0.65	90.14
5	تَوَقَّع	66	7.15	43.12	30	تَنَبُّؤ	5	0.54	90.68
6	مُتَغَيِّر	66	7.15	50.27	31	مُعْتاد	5	0.54	91.22
7	أَظْهَر	63	6.83	57.10	32	مُنْعَطَف	5	0.54	91.77
8	إِمْكانِيَّة	63	6.83	63.92	33	اِحْتِمال	5	0.54	92.31
9	حِوال	36	3.90	67.82	34	مُرْتَقَب	5	0.54	92.85
10	مُحْتَمَل	23	2.49	70.31	35	رُبَّما	4	0.43	93.28
11	قارَب	20	2.17	72.48	36	اعتماديه	4	0.43	93.72
12	اِفْتِراضِيّ	15	1.63	74.11	37	اِقْتَرَح	4	0.43	94.15
13	ما قَرُب	13	1.41	75.51	38	أَوْحَى	3	0.33	94.47
14	تَقْرِيب	13	1.41	76.92	39	اِفْتِراض	3	0.33	94.80
15	تَعَرَّض	11	1.19	78.11	40	اِقْتَرَب	3	0.33	95.12
16	اِعْتَقَد	10	1.08	79.20	41	مُنْتَظَر	3	0.33	95.45
17	عَدَم يَقِين	9	0.98	80.17	42	مُقارَبَة	3	0.33	95.77
18	تَراوَح	9	0.98	81.15	43	مُتَفاوِت	3	0.33	96.10
19	مُؤَقَّت	9	0.98	82.12	44	قُرابَة	3	0.33	96.42
20	وِقايَة	8	0.87	82.99	45	نادِر	2	0.22	96.64
21	اِسْتِباق	8	0.87	83.86	46	إِلَى حَدّ ما	2	0.22	96.86
22	مُتَحَفِّظ	8	0.87	84.72	47	إعادَة دِراسَة	2	0.22	97.07
23	مَعْقُول	8	0.87	85.59	48	إعادَة نَظَر	2	0.22	97.29
24	مُعْتَمَد عَلَى	8	0.87	86.46	49	مَبْدَئِيّ	2	0.22	97.51
25	بَدا	7	0.76	87.22	50	غُمُوض	2	0.22	97.72
All							1,103		

This table presents the most frequent uncertain sentiment words in Arabic CEO letters. The occurrences of the Arabic words were identified using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Arabic words Frequencies and cumulative percentages reflect lemma/token-level matches.

Appendix C.4 - English CEO Letters

Table C.4 (a-1) Most Frequent Positive Sentiment Words Occurring in the English CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	success	326	4.3	4.3	26	opportunity	93	1.23	60.77
2	opportunities	280	3.7	8.0	27	improvement	82	1.08	61.86
3	achieved	263	3.47	11.47	28	satisfaction	78	1.03	62.89
4	strong	263	3.47	14.95	29	improved	75	0.99	63.88
5	achieve	249	3.29	18.23	30	better	75	0.99	64.87
6	best	249	3.29	21.52	31	successfully	74	0.98	65.84
7	achieving	209	2.76	24.28	32	strengthen	73	0.96	66.81
8	leading	203	2.68	26.96	33	strength	66	0.87	67.68
9	innovation	201	2.65	29.61	34	strengthening	65	0.86	68.54
10	achievements	191	2.52	32.14	35	enhanced	62	0.82	69.36
11	efficiency	190	2.51	34.64	36	enabling	58	0.77	70.12
12	enhance	178	2.35	36.99	37	pleased	57	0.75	70.87
13	leadership	174	2.3	39.29	38	achievement	56	0.74	71.61
14	progress	173	2.28	41.58	39	enable	55	0.73	72.34
15	excellence	160	2.11	43.69	40	successes	54	0.71	73.05
16	despite	152	2.01	45.7	41	collaboration	52	0.69	73.74
17	highest	131	1.73	47.43	42	advantage	51	0.67	74.41
18	positive	128	1.69	49.12	43	confident	44	0.58	74.99
19	improve	125	1.65	50.77	44	strengthened	44	0.58	75.57
20	successful	122	1.61	52.38	45	enabled	43	0.57	76.14
21	innovative	120	1.58	53.96	46	efficient	42	0.55	76.7
22	enhancing	119	1.57	55.53	47	stable	42	0.55	77.25
23	exceptional	104	1.37	56.91	48	excellent	41	0.54	77.79
24	profitability	102	1.35	58.25	49	attractive	40	0.53	78.32
25	improving	98	1.29	59.55	50	improvements	37	0.49	78.81
All							7,556		

This table presents the most frequent positive sentiment words in English CEO letters. The occurrences of the English words were identified using Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Table C.4 (b-1) Most Frequent Negative Sentiment Words Occurring in the English CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	challenges	254	18.18	18.18	26	seize	10	0.72	61.42
2	loss	67	4.8	22.98	27	rationalization	9	0.64	62.06
3	challenging	53	3.79	26.77	28	concerned	8	0.57	62.63
4	against	44	3.15	29.92	29	easing	8	0.57	63.21
5	overcome	42	3.01	32.93	30	impairment	8	0.57	63.78
6	crisis	39	2.79	35.72	31	adverse	8	0.57	64.35
7	losses	36	2.58	38.3	32	restructure	8	0.57	64.92
8	difficult	30	2.15	40.44	33	threats	8	0.57	65.5
9	negative	25	1.79	42.23	34	postponing	7	0.5	66.0
10	claims	24	1.72	43.95	35	disrupted	7	0.5	66.5
11	restructuring	24	1.72	45.67	36	declined	7	0.5	67.0
12	crucial	22	1.57	47.24	37	complaints	6	0.43	67.43
13	obstacles	21	1.5	48.75	38	dropped	6	0.43	67.86
14	decline	20	1.43	50.18	39	crises	6	0.43	68.29
15	challenge	19	1.36	51.54	40	solvency	6	0.43	68.72
16	disruption	18	1.29	52.83	41	fraud	6	0.43	69.15
17	overcoming	15	1.07	53.9	42	severe	6	0.43	69.58
18	closure	15	1.07	54.97	43	serious	5	0.36	69.94
19	divestment	14	1.0	55.98	44	seizing	5	0.36	70.29
20	difficulties	14	1.0	56.98	45	exploit	5	0.36	70.65
21	deliberate	11	0.79	57.77	46	imperative	5	0.36	71.01
22	miss	11	0.79	58.55	47	catastrophe	5	0.36	71.37
23	disruptions	10	0.72	59.27	48	adversity	5	0.36	71.73
24	suffered	10	0.72	59.99	49	injuries	5	0.36	72.08
25	restated	10	0.72	60.7	50	suspension	5	0.36	72.44
All							1,419		

This table presents the most frequent negative sentiment words in English CEO letters. The occurrences of the English words were identified using Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Table C.4 (c-1) Most Frequent Uncertain Sentiment Words Occurring in the English CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	may	62	11.36	11.36	26	variables	4	0.73	86.45
2	risk	60	10.99	22.34	27	uncertain	4	0.73	87.18
3	possible	52	9.52	31.87	28	revised	4	0.73	87.91
4	believe	51	9.34	41.21	29	depends	3	0.55	88.46
5	risks	32	5.86	47.07	30	suggest	3	0.55	89.01
6	approximately	30	5.49	52.56	31	suggests	3	0.55	89.56
7	could	25	4.58	57.14	32	possibility	3	0.55	90.11
8	almost	20	3.66	60.81	33	predictive	3	0.55	90.66
9	anticipate	18	3.3	64.1	34	predict	3	0.55	91.21
10	nearly	17	3.11	67.22	35	contingency	3	0.55	91.76
11	precautionary	15	2.75	69.96	36	somewhat	3	0.55	92.31
12	uncertainty	12	2.2	72.16	37	unusual	2	0.37	92.67
13	believes	10	1.83	73.99	38	variants	2	0.37	93.04
14	fluctuations	8	1.47	75.46	39	dependent	2	0.37	93.41
15	exposure	7	1.28	76.74	40	depend	2	0.37	93.77
16	anticipated	6	1.1	77.84	41	cautiously	2	0.37	94.14
17	sudden	5	0.92	78.75	42	cautious	2	0.37	94.51
18	possibilities	5	0.92	79.67	43	reassess	2	0.37	94.87
19	perhaps	5	0.92	80.59	44	predictions	2	0.37	95.24
20	uncertainties	5	0.92	81.5	45	predicted	2	0.37	95.6
21	anticipation	5	0.92	82.42	46	probably	2	0.37	95.97
22	dependence	5	0.92	83.33	47	apparent	2	0.37	96.34
23	might	5	0.92	84.25	48	appear	2	0.37	96.7
24	depending	4	0.73	84.98	49	revise	1	0.18	96.89
25	believing	4	0.73	85.71	50	reassessing	1	0.18	97.07
All							587		

This table presents the most frequent uncertain sentiment words in English CEO letters. The occurrences of the English words were identified using Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Appendix C.5 - Negation Effect on Sentiment in Arabic and English Annual Reports

Table C.5(a-1) Negation in Arabic Financial Text: Negated-Negative Sentiment

Negation detection incident	Total	N-gram	Negation detection incident	Total	N-gram
عَدَم * وُجُود أَيّ * عارَض	379	1	لا * * تَدَخُّل	37	1
لا * * تَعارَض	348	1	عَدَم * وُجُود أَيّ * تَضارُب	29	1
لا * * ضَرّ	123	1	لا * * أَعْفَى	29	1
لا * وَجَد أَيّ * عُقُوبَة	121	1	دُون * تَكَبَّد * خَسارَة	29	1
لا * * خَضَع	118	1	لَم * * مَنَع	28	1
عَدَم * * مُبالَغَة	109	1	لا * * تَحَمَّل	28	1
دُون * * إِخْلال	109	1	دُون * * إِصابَة	26	1
لا * وَجَد * عارَض	101	1	غَيْر * * خاضِع	25	1
دُون * * تَأْخِير	97	1	عَدَم * * حَجْب مَعْلُومَة	8	2
عَدَم * وُجُود * عارَض	68	1	لا * أَثَّر * شَكْل سَلْبِيّ	6	2
لا * * غَطَّى	60	1	لَم * * تَمّ خَطَر	6	2
لا * وَجَد أَيّ * عارَض	60	1	لا * * اِسْتَغْنَى عَن	5	2
لا * * فات	58	1	غَيْر * دَقِيقَة أَو * غَيْر مُكْتَمَل	5	2
عَدَم * * إِخْلال	53	1	لَن * * تَمّ إِلْغاء	4	2
عَدَم * وُجُود * تَضارُب	47	1	غَيْر * مِن وَسِيلَة * تَمّ خَطَر	4	2
عَكْس * * خَسارَة	47	1	غَيْر * مِهْنِيّ أَو * غَيْر أَخْلاقِيّ	4	2
لا * جاز مُساهِم * مُطالَبَة	46	1	غَيْر * نِظامِيّ أَو * سُوء اِسْتِخْدام	4	2
لا * * تَعَدَّى	45	1	لا * اِعْتَبَر * عَدَم دَفْع	4	2
لَم * * فَرَض	44	1	غَيْر * مَشْرُوط * غَيْر قابِل إِلْغاء	6	3
دُون * * اِنْقِطاع	43	1	عَدَم * * مُبالَغَة فِي تَقْدِير	4	3
غَيْر * * مُضَلِّل	41	1	غَيْر * دَقِيقَة أَو * فِي غَيْر وَقْت	3	3
لَم * * رَفَض	40	1	عَدَم * اِعْتِماد * شَكْل غَيْر مُبَرِّر	2	3

The table provides examples of negated negative incidents detected in the Arabic annual reports. Each instance represents a sentiment word whose classification flipped to positive due to negation. N-gram column reflects the dimension of the sentiment word according to ArFinSD (e.g., مُبالَغَة فِي تَقْدِير is a 3-gram sentiment expression). The asterisk (*) reflects the negation scope captured by the model. For example, دُون * * اِنْقِطاع indicates that the sentiment word appears immediately after the negation form.

Table C.5(a-2) Negation in Arabic Financial Text: Negated-Positive Sentiment

Negation detection incident	Total	N-gram	Negation detection incident	Total	N-gram
لا * * تَجاوَز	759	1	لا * * شارَك	23	1
غَيْر * * رِبْحِيّ	173	1	لا * جاز أَنَّ * تَجاوَز	23	1
دُون * شَرْط أَو * مَزِيَّة	164	1	لا * * أَتاح	22	1
لَم * * تَقَدَّم	155	1	لا * * حَظِي	22	2
غَيْر * ذٰلِكَ مِن * مَزِيَّة	152	1	لا * أَثَّر * شَكْل كَبِير	6	2
غَيْر * مُباشِر عَلَى * رِبْحِيّ	135	1	لا * تَعَرَّض * صُورَة كَبِير	3	2
عَدَم * * تَجاوُز	99	1	لَيِس * مُعَرَّض * شَكْل كَبِير	2	2
عَدَم * * تَحْقِيق	81	1	غَيْر * مُعَرَّض * شَكْل كَبِير	2	2
لا * وَجَد * ضَمان	51	1	غَيْر * مَعْرِفَة * شَكْل كافِي	2	2
لا * أَمْكَن * تَأْكِيد	50	1	لَم * تَأَثَّر * شَكْل كَبِير	1	2
غَيْر * * مُكْتَسَب	45	1	لَم * * شَكْل مُسْتَمِرّ	1	2
لا * * تَقَدَّم	43	1	لَم * تَواصُل * شَكْل فَعّال	1	2
غَيْر * * مُحَقَّق	43	1	لَم * كان تَعامَل * صُورَة جَيِّد	1	2
لا * أَمْكَن * ضَمان	31	1	لا * * غَيْر مَسْبُوق	1	2
لا * وَجَد أَيّ * ضَمان	30	1	غَيْر * مَرْكَبَة * عَلَى رَغْم	1	2
دُون * * مَزِيَّة	30	1	غَيْر * مالِيّ * شَكْل سَلِس	1	2
دُون * أَيّ * مَزِيَّة	26	1	غَيْر * مُؤَكَّد * إِلَى حَدّ كَبِير	2	3
عَدَم * * مَكَّن	26	1	غَيْر * مُتَأَثِّر * إِلَى حَدّ كَبِير	1	3
لا * * تحفيز	24	1	غَيْر * عامِل أَدّ * إِلَى حَدّ كَبِير	1	3

The table provides examples of negated positive incidents detected in the Arabic annual reports. Each instance represents a sentiment word whose classification flipped to negative due to negation. N-gram column reflects the dimension of the sentiment word according to ArFinSD (e.g., مُبالَغَة فِي تَقْدِير is a 3-gram sentiment expression). The asterisk (*) reflects the negation scope captured by the model. For example, دُون * * إِنْقِطاع indicates that the sentiment word appears immediately after the negation form.

Table C.5(b-1) Negation in English Financial Text: Negated-Negative Sentiment

Negation detection incident	Total	Negation detection incident	Total
not * * conflict	208	not * * adversely	11
not * * harm	104	not * been * restated	10
not * * exposed	85	not * absolute assurance * against	9
not * * contradict	53	not * * jeopardize	8
not * cause any * conflict	21	not * be * disrupted	7
not * * misleading	21	not * constitute a * breach	7
not * * disclose	21	not * * subjected	7
not * * prejudice	20	not * * miss	7
not * significantly * exposed	14	not * * revoke	7
not * * rejected	14	not * include * restructuring	7
not * * violate	14	not * predict * adverse	7
not * * contrary	14	not * reported * claims	7
not * * disclosed	13	not * * exploit	6
not * * exaggerating	13	not * to * violate	6
not * * negatively	13	not * * restated	6
not * * reject	12	not * responsible for * misuse	6
not * * lose	12	not * result in * loss	6
not * * fail	11	not * * neglect	6
not * * tolerate	11	not * * losing	6
not * * refuse	11	not * * confined	6

The table provides examples of negated negative incidents detected in the English annual reports. Each instance represents a sentiment word whose classification flipped to positive due to negation. The sentiment analysis is conducted using the Loughran and McDonald (LM) Dictionary. The asterisk (*) reflects the negation scope captured by the model. For example, (not * * tolerate) indicates that the sentiment word appears immediately after the negation form.

Table C.5(b-2) Negation in English Financial Text: Negated-Positive Sentiment

Negation detection incident	Total	Negation detection incident	Total
not * * achieve	57	not * able to * adequately	4
not * * satisfied	11	not * be * easily	4
not * * achieving	11	not * * good	4
not * * resolve	9	not * * satisfy	4
not * have * achieved	8	not * have the * opportunity	4
not * * achieved	8	not * * enjoy	4
not * * assure	8	never * * satisfied	4
not * * informative	6	not * guarantee the * innovations	3
not * have been * achieved	6	not * require * improvements	3
not * driven by * creative	6	not * * innovate	3
not * conclude * exclusively	6	not * * rewarded	3
not * * reward	6	not * * easily	3
not * * succeed	6	not * be * successful	3
not * only * enhance	5	not * be * assured	3
not * * adequately	5	not * simply a * charitable	2
not * * succeeding	4		

The table provides examples of negated positive incidents detected in the English annual reports. Each instance represents a sentiment word whose classification flipped to negative due to negation. The sentiment analysis is conducted using the Loughran and McDonald (LM) Dictionary. The asterisk (*) reflects the negation scope captured by the model. For example, (not * * reward) indicates that the sentiment word appears immediately after the negation form.

Appendix C.6 - Cross-Classification Differences: ArFinSD and ArSenL

Table C. 6 (a-1) Cross-Classification Differences: Negative (ArFinSD) and Positive (ArSenL)

		Words *N=205*			
آل	تَحْذِير	دِفاعِيّ	كَفَّل	مُغالاة	ٱلْتِماس
أَثار	تَحْرِيض	ذَعِن	لَها	مُغْرِض	ٱنْتِهازِيّ
أَجَّل	تَحْرِيف	رَيْب	مَتْرُوك	مُنْتَهَك	ٱنْتِهاك
أَجْبَر	تَخاصَم	سَحْنَة	مَحْمَل	مُنْحَرِف	ٱنْحِراف
أَحال	تَراخِي	سَخَّر	مَدْعاة	مُنْكَمِش	ٱنْقَضَى
أَخْمَد	تَرَوِّي	سَلَّم	مَزْعَمَة	مِحْنَة	تَبْرِئَة
أَذْعَن	تَرْشِيد	سُوء	مَشَى	مِحْوَرِيّ	تَجادَل
أَرْشَد	تَساءَل	شاذّ	مَعْرِض	نَبَّه	تَجْمِيد
أَرْغَم	تَسْرِيح	شَكّ	مَعْزُول	نَحَّى	تَحايُل
أَعاق	تَشْدِيد	شَهَر	مَنَع	نَفَر	تَحَدِّي
أَلْزَم	تَشْوِيه	صارِم	مَهْجُور	نُضُوب	تَحَمُّل
وَخِّر	تَعَسُّفِيّ	صَفَّى	مُؤاخَذ	هَدْم	تَحَوُّط
إِبْراء	تَقَشُّف	ضَخَّم	مُؤامَرَة	هَزِيل	خاطَر
إِبْطال	تَمَرُّد	ضَرُورِيّ	مُبالَغَة	هَشّ	خانَق
إِحْجام	تَوَسَّل	ضِدّ	مُبْهَم	وَشِيك	خَبَث
إِخْلاء	تَوَقُّف	عَبَث	مُتَأَهِّب	وَقاحَة	خَضَع
إِذْعان	ثُغْرَة	عَشْوائِيّ	مُتَخَلِّف	وَهِم	خَفَق
إِرْغام	جادَل	عَصِيب	مُتَساهِل	ٱتَّهَم	خُضُوع
إِسْعاف	جَدَل	عُقُوبَة	مُتَعَثِّر	ٱحْتَجَز	دَقَّق
إِعْراض	جَدّال	عِصْيان	مُتَعَمَّد	ٱحْتَكَر	قَسْر
إِفْراج	جَسِيم	غالِي	مُتَفَشِّي	ٱحْتِراز	قَسْرِيّ
إِفْساد	جَلَى	غَرامَة	مُتَقَلِّب	ٱخْتَلَف	قَصْر
إِفْشاء	جُنُوح	غَطَّى	مُتَوَرِّط	ٱدِّعاء	قَطَع
إِقالَة	حادّ	غَفَر	مُتْعَب	ٱرْتِباك	قَلَّل
إِكْراه	حَبَس	غِشّ	مُثَقَّل	ٱسْتَبْعَد	قَهْر
إِلْزامِيّ	حَتْمِيّ	فات	مُحَطِّم	ٱسْتَدْعَى	كَبَح
إِنْقاذ	حَجْب	فارّ	مُحْتَجَز	ٱسْتَقْصَى	مُصالَحَة
بالَغ	حَرَم	فَجْوَة	مُخْتَلَس	ٱسْتَوْقَف	مُصَحِّح
بالِغ	حَصَر	فَساد	مُرابِي	ٱسْتَوْلَى	مُطَوَّل
بَراءَة	حَمَل	فَصْل	مُرْهِق	ٱسْتِحالَة	مُعاقَبَة
بَرَّأ	حَمْل	قابِلِيَّة	مُزَعْزَع	ٱسْتِدْعاء	مُعاكِس
بَطَل	حِذْر	قَبِل	مُسْتَبْدَل	ٱسْتِرْضاء	مُعَلَّق
تَأْدِيب	حِيطَة	قَدِيم	مُسْتَهْتَر	ٱسْتِنْزاف	مُعْتَرَف
ٱعْتَرَف	ٱعْتِزال	ٱفْتَقَر	ٱكْتِراث	ٱسْتِيلاء	ٱلْتَمَس
					ٱلْتِفاف

The table represents a list of negative words according to Arabic Financial Sentiment Dictionary (ArFinSD) that received a positive dominant sentiment classification in the Arabic Sentiment Lexicon, ArSenL.

Table C. 6 (a-2) Cross-Classification Differences: Negative (ArFinSD) and Neutral (ArSenL)

Words *N=232*					
أَرْجَأ	تَحَيَّز	جَمَّد	عَزَل	مُحاكَمَة	ٱسْتَجْوَب
أَضْحَى	تَخَلّص	جُنْحَة	عَقَبَة	مُحْتَجّ	ٱسْتَنْفَد
أَطال	تَخَلَّف	حاجِز	عَكْس	مُحْتَكِر	ٱسْتِبْدال
أَعْفَى	تَخْفِيض	حَجْز	عَنِيف	مُخالَصَة	ٱسْتِسْلام
أَغْضَب	تَخْفِيف	حَذَف	عُنْف	مُخْتَرَق	ٱسْتِغْلال
أَغْلَق	تَداخُل	حَذْف	عِقاب	مُدَّعِي	ٱسْتِقالَة
أَفْشَى	تَداعِي	حَظَر	غِياب	مُسْتَدْعَى	ٱسْتِقْصاء
أَقْسَى	تَدَخَّل	حَظّر	فادِح	مُشَدِّد	ٱسْتِنْفار
أَمَر	تَدَخُّل	حَنِث	فَسَخ	مُصادَرَة	ٱشْتِباه
أَنْهَى	تَذَبْذَب	حَيَّد	فَسْخ	مُطالَبَة	ٱصْطِدام
أَوْرَط	تَذَرَّع	خَطَر	قاطَع	مُعاد	ٱضْطَرّ
إِبْعاد	تَراجَع	خَلَط	قَذْف	مُعارِض	ٱعْتَقَل
إِجْبار	تَرَدَّد	رَشا	قَسَر	مُعَرْقِل	ٱعْتِقال
إِجْهاد	تَزْوِير	رَشْوَة	قَمْع	مُعْتَرِض	ٱفْتِراء
إِحْراق	تَزْيِيف	رَكَد	كَبَت	مُعْتَقَل	ٱقْتَرَف
إِحْلال	تَشْتِيت	رُضُوخ	كَبْح	مُقاضاة	ٱكْتَشَف
إِخْفاء	تَصْعِيد	زَيَّف	كَذّب	مُقاطَعَة	ٱمْتِعاض
إِزاحَة	تَعَثّر	سَأَل	كَساد	مُقَلّص	ٱمْتِناع
إِزالَة	تَعَجَّل	سَجَن	كَسُول	مُكَلَّف	ٱنْتَزَع
إِطالَة	تَعَدَّى	سَجِين	كَفالَة	مُلِحّ	ٱنْتَقَص
إِعاقَة	تَعْدِيل	سَرِي	كِذْب	مُلْتَبِس	ٱنْتِزاع
إِعْتام	تَعْطِيل	سَيَّل	مَحا	مُنافِس	ٱنْتِكاس
إِغْلاق	تَغَلَّب	سُخْرِيَّة	مَحْبُوس	مُناوِئ	ٱنْحِدار
إِقْفال	تَغَيُّب	سُدّ	مَحْظُور	مُنْحَدَر	ٱنْحِسار
إِلْزام	تَفادَى	شَحّ	مَدْيُون	مُنْحَلّ	ٱنْخَفَض
إِلْغاء	تَفَشّي	صادَر	مَزّاح	مُنْقَطِع	ٱنْخِفاض
إِنْهاء	تَقاضِي	صَعَّد	مَشُوش	نافَس	ٱنْزِلاق
بَرَّر	تَقَصَّى	صِراع	مَصِير	نَحَل	ٱنْفَصَل
بَطّأ	تَقَلّص	ضَغَط	مَقْطُوع	نَصَّف	ٱنْفِصال
تَآكَل	تَقْلِيص	طالَب	مَقْعَد	نِزاع	ٱنْقِباض
تَآكُل	تَقْلِيل	طَرَد	مَمْنُوع	هارِب	ٱنْقِطاع
تَآمُر	تَكاسَل	طَرْد	مَنْزُوع	هَجْر	ٱنْكِماش
تَأْجِيل	تَمَلَّص	طَلاق	مَنْع	وِقائِيّ	
تَأْخِير	تَمْحِيص	عاق	مَوْقُوف	ٱحْتِجاج	
تَثاقُل	تَنازُل	عاقَب	مُتَآمِر	ٱحْتِجاز	
تَجاهُل	تَهاوَى	عاقِبَة	مُتَحَيِّز	ٱخْتِراق	
تَجْرِيد	تَهَرَّب	عالِق	مُتَذَبْذِب	ٱخْتِفاء	
تَحَرَّى	تَواطَأ	عَدُوّ	مُتَّهَم	ٱدَّعَى	
تَحَرُّش	تَواطُؤ	عَرْقَل	مُجْحِف	ٱرْتَكَب	
تَحَرِّي	تَوَسُّل	عَرْقَلَة	مُجْهَد	ٱرْتِكاب	

The table represents a list of negative words according to Arabic Financial Sentiment Dictionary (ArFinSD) that received a neutral dominant sentiment classification in the Arabic Sentiment Lexicon, ArSenL.

Table C. 6 (a-3) Cross-Classification Differences: Positive (ArFinSD) and Negative (ArSenL)

Words *N=45*				
أَحَلّ	تَضافُر	زاخِر	مَضْمُون	فاق
أَسْبَقِيَّة	تَعافَى	غَزِير	مَوات	واثِق
أَقْصَى	تَعافِي	مُبْتَهِج	يَسِير	وافِر
أَنْجَز	تَفَوَّق	مُتَجاوِز	اِئْتِلاف	وَفِير
أَيْسَر	تَوْطِيد	مُتَّقِن	اِبْتَكَر	وَلاء
إِبْداع	حَصْرِيّ	مُدْهِش	اِخْتَرَع	
بَرَع	حَفَز	مُسْتَقِرّ	اِرْتِياح	
تَآزُر	حَلّ	مُنْتَظِم	اِسْتِعادَة	
تَجاوَز	رَخاء	مُنْدَهِش	اِنْتَعَش	
تَشْجِيع	رَغْم	مُنْفَتِح	هَيِّن	

The table represents a list of positive words according to Arabic Financial Sentiment Dictionary (ArFinSD) that received a negative dominant sentiment classification in the Arabic Sentiment Lexicon, ArSenL.

Table C. 6 (a-4) Cross-Classification Differences: Positive (ArFinSD) and Neutral (ArSenL)

Words *N=50*				
أَسْعَد	تَفَرُّد	شارَك	مَشْرِق	مِفَضّ
أَسْنَد	تَكاثُف	ضامِن	مُتَطَوِّر	نَزاهَة
أَمَّن	جاوَز	ضَمان	مُحْرِز	نَما
أَمْتَع	جَنَى	طَفْرَة	مُسْتَفِيد	نُمُوّ
بَهَر	حِلْف	عَرِيق	مُسْتَهْدَف	هادِف
تَحالُف	رائِج	غَزارَة	مُقْنِع	اِجْتاز
تَشْوِيق	راسِخ	كافَأ	مُكْتَسَب	اِسْتَعاد
تَطْوِير	رَسَّخ	مَجّانِيّ	مُلْفِت	اِنْتَفَع
تَعاوَن	رَواج	مَدَر	مُنْتَصِر	اِنْتِشار
تَعاوُن	شائِع	مَرْجُوّ	مُنْجَز	اِنْتِعاش

The table represents a list of positive words according to Arabic Financial Sentiment Dictionary (ArFinSD) that received a neutral dominant sentiment classification in the Arabic Sentiment Lexicon, ArSenL.

Table C. 6 (a-5) Cross-Classification Differences: Uncertain (ArFinSD) and Positive (ArSenL)

Words *N=59*				
أَظْهَر	تَقْرِيب	رَيْب	مُتَغَيِّر	اِتِّكال
أَوْحَى	تَكَهَّن	شاذّ	مُتَقَلِّب	اِحْتِراز
إِمْكانِيَّة	تَكَهُّن	شَكّ	مُتَوَقَّع	اِخْتَلَف
إِيضاح	تَوَقُّع	صُدْفَة	مُحْتَرِس	اِرْتِباك
تَبَعِيَّة	تَوَقُّف	ظاهِر	مُرَجّح	اِرْتِياب
تَحَسُّب	تَوْضِيح	عَشْوائِيّ	مُرْتَقَب	اِسْتِباق
تَرَقُّب	جَهْل	قابِلِيَّة	مُعَلّق	اِعْتَقَد
تَرَقَّب	حِذْر	قَدَّر	مُعْتاد	اِعْتِباطِيّ
تَعَسُّفِيّ	حِيطَة	مَبْدَئِيّ	مُفْتَرَض	اِعْتِباطِيَّة
تَعْلِيق	خاطَر	مَعْقُول	مُقارَبَة	اِقْتَرَح
تَغَيَّر	خَفِيّ	مُبْهَم	مُنْتَظَر	اِنْحِراف
تَقَلّب	راجَع	مُتَحَفِّظ	مُنْحَرِف	

The table represents a list of uncertain words according to Arabic Financial Sentiment Dictionary (ArFinSD) that received a positive dominant sentiment classification in the Arabic Sentiment Lexicon, ArSenL.

Table C. 6 (a-6) Cross-Classification Differences: Uncertain (ArFinSD) and Neutral (ArSenL)

Words *N=28*				
إِشاعَة	تَعْطِيل	حِوال	مَجْهُول	وِقائِيّ
بَدا	تَقارَب	خَطَر	مَشُوش	اِحْتِمال
تَداخُل	تَقْرِيبِيّ	دَنا	مُتَذَبْذِب	اِسْتَبَق
تَذَبْذَب	تَمْهِيدِيّ	رُبَّما	مُفْتَرَق	اِنْتَظَر
تَرَدَّد	تَنَبَّأ	عالِق	مُلْتَبِس	
تَعْدِيل	تَنَبُّؤ	قارَب	مُنْعَطَف	

The table represents a list of uncertain words according to Arabic Financial Sentiment Dictionary (ArFinSD) that received a neutral dominant sentiment classification in the Arabic Sentiment Lexicon, ArSenL.

Appendix C.7 - Arabic General Sentiment Dictionary (ArSenL) - Annual Reports

Table C.7 (a-1) Most Frequent Positive Sentiment Words Occurring in the Arabic Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	عَلَى	149,657	5.58	5.58	26	تَقْدِيم	13,275	0.5	30.85
2	إدارَة	106,380	3.97	9.55	27	جَدِيد	13,234	0.49	31.34
3	مالِيّ	53,544	2.0	11.55	28	كَبِير	13,012	0.49	31.82
4	عَمَل	53,094	1.98	13.53	29	ذات	12,937	0.48	32.31
5	تَمّ	43,413	1.62	15.15	30	مُسْتَوَى	12,835	0.48	32.79
6	خِدْمَة	28,229	1.05	16.2	31	إِسْتراتِيجِيّ	12,518	0.47	33.25
7	نِظام	28,221	1.05	17.26	32	حَقّ	12,480	0.47	33.72
8	مُكافَأَة	25,316	0.94	18.2	33	تَعْزِيز	11,499	0.43	34.15
9	مَجْمُوعَة	23,539	0.88	19.08	34	تَوْزِيع	11,492	0.43	34.58
10	قِيمَة	22,255	0.83	19.91	35	مَشْرُوع	11,492	0.43	35.01
11	كان	22,183	0.83	20.74	36	بَيّن	11,312	0.42	35.43
12	داخِلِيّ	21,898	0.82	21.56	37	مال	11,197	0.42	35.85
13	تَنْفِيذِيّ	21,724	0.81	22.37	38	عَقْد	10,987	0.41	36.26
14	قِطاع	20,875	0.78	23.14	39	سِعْر	10,952	0.41	36.66
15	سِياسَة	20,504	0.77	23.91	40	خُطّة	10,802	0.4	37.07
16	هَدَف	19,347	0.72	24.63	41	عَرَبِيّ	10,729	0.4	37.47
17	رِبْح	19,229	0.72	25.35	42	رَئِيس	10,708	0.4	37.87
18	مُساهِم	19,137	0.71	26.06	43	تَحْدِيد	10,651	0.4	38.26
19	عَمِيل	18,944	0.71	26.77	44	شَأْن	10,528	0.39	38.66
20	أَداء	18,831	0.7	27.47	45	مَرْكَز	10,523	0.39	39.05
21	تَحْقِيق	16,828	0.63	28.1	46	رَئِيسِيّ	10,490	0.39	39.44
22	اِلْتِزام	16,393	0.61	28.71	47	قُدْرَة	10,216	0.38	39.82
23	نَشاط	15,911	0.59	29.31	48	مَصْلَحَة	10,148	0.38	40.2
24	تَقْيِيم	14,426	0.54	29.84	49	وَجَد	9,904	0.37	40.57
25	تَوْصِيَة	13,583	0.51	30.35	50	مَسْؤُولِيَّة	9,881	0.37	40.94
All							2,639,655		

This table presents the most frequent positive sentiment words, identified in the Arabic annual reports. The occurrences of Arabic words were calculated using the ArSenL dictionary, which was converted into a dominant sentiment orientation. Sentiment words with equal negativity and positivity scores were classified as neutral. The dictionary contains lemma entries, and duplicate lemmas are resolved by relying on the average score of the sentiment.

Table C.7 (b-1) Most Frequent Negative Sentiment Words Occurring in the Arabic Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	ما	42,246	4.14	4.14	26	حَدّ	7,219	0.71	37.33
2	عامّ	36,929	3.62	7.76	27	خارِجِيّ	6,988	0.69	38.02
3	كَما	22,636	2.22	9.98	28	اِجْتِماعِيّ	6,871	0.67	38.69
4	قام	21,068	2.07	12.05	29	مُسْتَمِرّ	6,716	0.66	39.35
5	مَمْلَكَة	20,390	2.00	14.05	30	تَوْفِير	6,432	0.63	39.98
6	إِجْراء	18,671	1.83	15.88	31	طَلَب	6,312	0.62	40.60
7	سَنَوِيّ	17,382	1.70	17.58	32	مُعَدَّل	6,115	0.60	41.20
8	مِلْيُون	16,748	1.64	19.23	33	رَقَمِيّ	5,953	0.58	41.79
9	تارِيخ	14,664	1.44	20.67	34	عادِيّ	5,849	0.57	42.36
10	سَهْم	14,425	1.41	22.08	35	حَلّ	5,748	0.56	42.92
11	مِعْيار	13,259	1.30	23.38	36	قائِم	5,685	0.56	43.48
12	خاصّ	13,129	1.29	24.67	37	جانِب	5,541	0.54	44.02
13	أُخْرَى	12,511	1.23	25.89	38	قاعِدَة	5,515	0.54	44.56
14	تِجارِيّ	11,168	1.10	26.99	39	رُؤْيَة	5,495	0.54	45.10
15	عَدَد	10,559	1.04	28.02	40	مَوْجُود	5,206	0.51	45.61
16	بُعْد	9,938	0.97	29.00	41	تَأْثِير	5,150	0.51	46.12
17	اِجْتِماع	9,840	0.96	29.96	42	سابِق	5,055	0.50	46.61
18	عالَمِيّ	9,406	0.92	30.89	43	مُقارَنَة	5,003	0.49	47.11
19	تابِع	9,069	0.89	31.78	44	مَحْدُود	4,622	0.45	47.56
20	تَكْلِيف	9,024	0.88	32.66	45	رِعايَة	4,617	0.45	48.01
21	وَضْع	8,874	0.87	33.53	46	عَدِيد	4,614	0.45	48.46
22	لَدَى	8,512	0.83	34.37	47	اِحْتِياطِيّ	4,407	0.43	48.90
23	قائِمَة	8,288	0.81	35.18	48	مِلْيار	4,364	0.43	49.32
24	خَسارَة	7,431	0.73	35.91	49	تَأَكُّد	4,285	0.42	49.74
25	حالِيّ	7,340	0.72	36.63	50	طَوِيل	4,284	0.42	50.16
All							1,004,882		

This table presents the most frequent negative sentiment words, identified in the Arabic annual reports. The occurrences of Arabic words were calculated using the ArSenL dictionary, which was converted into a dominant sentiment orientation. Sentiment words with equal negativity and positivity scores were classified as neutral. The dictionary contains lemma entries, and duplicate lemmas are resolved by relying on the average score of the sentiment.

Table C.7 (c-1) Most Frequent Neutral Sentiment Words Occurring in the Arabic Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	فِي	235,177	10.74	10.74	26	زِيادَة	12,808	0.58	47.07
2	شَرِكَة	185,032	8.45	19.19	27	نَتِيجَة	12,325	0.56	47.63
3	مَجْلِس	73,219	3.34	22.53	28	لائِحَة	12,062	0.55	48.18
4	الَّذِي	71,113	3.25	25.78	29	إِضافَة	11,986	0.55	48.73
5	لَجْنَة	43,890	2.00	27.78	30	نُمُوّ	11,890	0.54	49.27
6	عُضْو	37,051	1.69	29.47	31	تَنْفِيذ	11,383	0.52	49.79
7	عام	36,377	1.66	31.13	32	بَلَغ	11,222	0.51	50.30
8	مُراجَعَة	36,204	1.65	32.79	33	مَبْلَغ	10,997	0.50	50.80
9	أَيّ	29,430	1.34	34.13	34	مَعْلُومَة	10,319	0.47	51.27
10	سَعُودِيّ	23,489	1.07	35.20	35	رَقابَة	10,139	0.46	51.74
11	سُوق	21,768	0.99	36.20	36	بِناء	10,006	0.46	52.19
12	عَمَلِيَّة	20,437	0.93	37.13	37	رَأْس	9,637	0.44	52.63
13	تَقْرِير	18,972	0.87	38.00	38	قَرار	9,561	0.44	53.07
14	شَكْل	18,190	0.83	38.83	39	تَمْوِيل	8,444	0.39	53.46
15	بَنْك	18,103	0.83	39.65	40	ضَمان	8,432	0.39	53.84
16	نِسْبَة	16,528	0.75	40.41	41	مُتَعَلِّق	8,297	0.38	54.22
17	ٱِسْتِثْمار	16,219	0.74	41.15	42	دَوْلِيّ	7,885	0.36	54.58
18	مُوَظَّف	16,191	0.74	41.89	43	مَوْرِد	7,765	0.35	54.94
19	تَطْوِير	15,819	0.72	42.61	44	إِعادَة	7,599	0.35	55.28
20	جَمْعِيَّة	15,251	0.70	43.31	45	ٱِسْتِخْدام	7,301	0.33	55.62
21	سَنَة	14,521	0.66	43.97	46	تَرْشِيح	7,153	0.33	55.94
22	مُنْتَج	14,412	0.66	44.63	47	جِهَة	7,074	0.32	56.27
23	كُلّ	13,678	0.62	45.25	48	مُخْتَلِف	6,981	0.32	56.58
24	بَرْنامَج	13,502	0.62	45.87	49	أَكْثَر	6,954	0.32	56.90
25	تَأْمِين	13,387	0.61	46.48	50	صادِر	6,886	0.31	57.22
All							2,190,067		

This table presents the most frequent neutral sentiment words, identified in the Arabic annual reports. The occurrences of Arabic words were calculated using the ArSenL dictionary, which was converted into a dominant sentiment orientation. Sentiment words with equal negativity and positivity scores were classified as neutral. The dictionary contains lemma entries, and duplicate lemmas are resolved by relying on the average score of the sentiment.

Appendix C.8 - Arabic General Sentiment Dictionary (ArSenL) - CEO Letters

Table C.8 (a-1) Most Frequent Positive Sentiment Words Occurring in the Arabic CEO Letters

Rank					Rank				
	Word	Total	%	Cum %		Word	Total	%	Cum %
1	عَلَى	4,451	5.93	5.93	26	مُساهِم	417	0.56	30.40
2	عَمَل	1,685	2.25	8.18	27	تَحْسِين	398	0.53	30.93
3	خِدْمَة	1,367	1.82	10.00	28	نَحْو	395	0.53	31.46
4	قِطاع	1,107	1.48	11.48	29	إِيراد	388	0.52	31.97
5	تَحْقِيق	1,094	1.46	12.94	30	فُرْصَة	384	0.51	32.49
6	عَمِيل	1,000	1.33	14.27	31	إِنْجاز	384	0.51	33.00
7	جَدِيد	890	1.19	15.46	32	مَشْرُوع	379	0.51	33.50
8	مَجْمُوعَة	764	1.02	16.47	33	تَشْغِيلِيّ	376	0.50	34.01
9	تَعْزِيز	761	1.01	17.49	34	اِلْتِزام	373	0.50	34.50
10	إِدارَة	754	1.01	18.49	35	قُدْرَة	370	0.49	35.00
11	إِسْتراتِيجِيّ	718	0.96	19.45	36	أَفْضَل	366	0.49	35.48
12	هَدَف	654	0.87	20.32	37	شَهِد	364	0.49	35.97
13	أَداء	652	0.87	21.19	38	رَئِيس	359	0.48	36.45
14	كان	640	0.85	22.05	39	إِجْمالِيّ	356	0.47	36.92
15	مُسْتَوَى	628	0.84	22.88	40	عَرَبِيّ	354	0.47	37.39
16	مالِيّ	628	0.84	23.72	41	رِبْح	352	0.47	37.86
17	دَعْم	613	0.82	24.54	42	صِحِّيّ	343	0.46	38.32
18	قِيمَة	608	0.81	25.35	43	تَحَدِّي	343	0.46	38.78
19	مَجال	526	0.70	26.05	44	كَفاءَة	325	0.43	39.21
20	نَجاح	493	0.66	26.71	45	عَبْر	316	0.42	39.63
21	كَبِير	490	0.65	27.36	46	تَنْفِيذِيّ	311	0.41	40.05
22	حَقَّق	485	0.65	28.01	47	إِسْتراتِيجِيَّة	310	0.41	40.46
23	تَمّ	480	0.64	28.65	48	تَحَوُّل	309	0.41	40.87
24	جَهْد	479	0.64	29.28	49	فَضْل	300	0.40	41.27
25	تَقْدِيم	420	0.56	29.84	50	قُوَّة	299	0.40	41.67
All							74,535		

This table presents the most frequent positive sentiment words, identified in the Arabic CEO letters. The occurrences of Arabic words were calculated using the ArSenL dictionary, which was converted into a dominant sentiment orientation. Sentiment words with equal negativity and positivity scores were classified as neutral. The dictionary contains lemma entries, and duplicate lemmas are resolved by relying on the average score of the sentiment.

Table C.8 (b-1) Most Frequent Negative Sentiment Words Occurring in the Arabic CEO Letters

Rank					Rank				
	Word	Total	%	Cum %		Word	Total	%	Cum %
1	عامّ	1,168	4.11	4.11	26	رَغْم	210	0.74	39.15
2	مَمْلَكَة	1,029	3.62	7.72	27	تَكْلِيف	209	0.73	39.88
3	ما	1,007	3.54	11.26	28	اِجْتِماعِيّ	205	0.72	40.60
4	كَما	848	2.98	14.25	29	مَكانَة	205	0.72	41.32
5	مِلْيُون	687	2.42	16.66	30	مُسْتَدام	194	0.68	42.01
6	رَقَمِيّ	525	1.85	18.51	31	سَنَوِيّ	192	0.68	42.68
7	عالَمِيّ	451	1.59	20.09	32	تَوْفِير	188	0.66	43.34
8	رُؤْيَة	372	1.31	21.40	33	سَعَى	187	0.66	44.00
9	مِلْيار	367	1.29	22.69	34	مُعَدَّل	184	0.65	44.65
10	مُسْتَمِرّ	357	1.26	23.95	35	وَلاء	179	0.63	45.27
11	قام	333	1.17	25.12	36	لَدَى	177	0.62	45.90
12	عَدَد	326	1.15	26.26	37	حالِيّ	170	0.60	46.49
13	مُقارَنَة	304	1.07	27.33	38	طَوِيل	166	0.58	47.08
14	رِعايَة	301	1.06	28.39	39	حِفاظ	166	0.58	47.66
15	بُعْد	290	1.02	29.41	40	طَلَب	159	0.56	48.22
16	عَدِيد	289	1.02	30.42	41	مِعْيار	157	0.55	48.77
17	خاصّ	288	1.01	31.44	42	أَصْبَح	154	0.54	49.31
18	حَلّ	275	0.97	32.40	43	إِجْراء	150	0.53	49.84
19	شُكْر	267	0.94	33.34	44	رِحْلَة	142	0.50	50.34
20	تِجارِيّ	266	0.94	34.28	45	فَرْد	139	0.49	50.83
21	جائِح	265	0.93	35.21	46	وَضْع	138	0.49	51.31
22	عالَم	246	0.86	36.07	47	مَسِيرَة	137	0.48	51.80
23	شَرِيك	238	0.84	36.91	48	قاعِدَة	136	0.48	52.27
24	ماضِي	215	0.76	37.67	49	مُتَوَسِّط	134	0.47	52.75
25	جانِب	211	0.74	38.41	50	أُخْرَى	134	0.47	53.22
All							28,180		

This table presents the most frequent negative sentiment words, identified in the Arabic CEO letters. The occurrences of Arabic words were calculated using the ArSenL dictionary, which was converted into a dominant sentiment orientation. Sentiment words with equal negativity and positivity scores were classified as neutral. The dictionary contains lemma entries, and duplicate lemmas are resolved by relying on the average score of the sentiment.

Table C.8 (c-1) Most Frequent Neutral Sentiment Words Occurring in the Arabic CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	فِي	8,681	15.38	15.38	26	مُسْتَقْبَل	300	0.53	49.03
2	شَرِكَة	3,287	5.82	21.20	27	تَنْفِيذ	296	0.52	49.55
3	الَّذِي	2,221	3.93	25.14	28	مَحَلِّيّ	271	0.48	50.03
4	عام	2,114	3.75	28.88	29	تَوَسُّع	269	0.48	50.51
5	نُمُوّ	1,132	2.01	30.89	30	تَنْمِيَة	245	0.43	50.94
6	تَطْوِير	725	1.28	32.17	31	سَنَة	242	0.43	51.37
7	نِسْبَة	699	1.24	33.41	32	تَجْرِبَة	238	0.42	51.79
8	سُوق	693	1.23	34.64	33	بِناء	236	0.42	52.21
9	سَعُودِيّ	643	1.14	35.78	34	مِنَصَّة	233	0.41	52.62
10	زِيادَة	606	1.07	36.85	35	وَصَل	229	0.41	53.03
11	اِسْتِثْمار	584	1.03	37.89	36	إِعادَة	216	0.38	53.41
12	مُنْتَج	538	0.95	38.84	37	تَوْسِيع	216	0.38	53.79
13	مُوَظَّف	531	0.94	39.78	38	مَزِيد	212	0.38	54.17
14	عَمَلِيَّة	526	0.93	40.71	39	عُضْو	209	0.37	54.54
15	تَأْمِين	486	0.86	41.57	40	مُخْتَلِف	206	0.36	54.91
16	بَرْنامَج	466	0.83	42.40	41	إِنْتاج	203	0.36	55.27
17	بَلَغ	433	0.77	43.17	42	دَوْلِيّ	200	0.35	55.62
18	أَكْثَر	420	0.74	43.91	43	مُواصَلَة	200	0.35	55.97
19	شَكْل	394	0.70	44.61	44	اِسْتِمْرار	194	0.34	56.32
20	واصَل	393	0.70	45.30	45	بَشَرِيّ	190	0.34	56.65
21	إِضافَة	390	0.69	45.99	46	وَطَنِيّ	189	0.33	56.99
22	كُلّ	374	0.66	46.66	47	مَوْقِع	188	0.33	57.32
23	نَتِيجَة	367	0.65	47.31	48	تَمَكَّن	187	0.33	57.65
24	مَجْلِس	347	0.61	47.92	49	مَوْرِد	186	0.33	57.98
25	بَنْك	324	0.57	48.50	50	تَقْرِير	185	0.33	58.31
All							56,446		

This table presents the most frequent neutral sentiment words, identified in the Arabic CEO letters. The occurrences of Arabic words were calculated using the ArSenL dictionary, which was converted into a dominant sentiment orientation. Sentiment words with equal negativity and positivity scores were classified as neutral. The dictionary contains lemma entries, and duplicate lemmas are resolved by relying on the average score of the sentiment.

Appendix C.9 - Translated-Arabic Annual Reports

Table C.9 (a-1) Most Frequent Positive Sentiment Words Occurring in the Translated-Arabic Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	تَطْوِير	15,337	5.51	5.51	26	مَزِيَّة	2,661	0.96	60.43
2	تَحْقِيق	14,133	5.08	10.58	27	ٱِسْتِفادَة	2,640	0.95	61.38
3	نُمُوّ	11,286	4.05	14.64	28	رِبْحِيّ	2,360	0.85	62.23
4	تَعْزِيز	11,083	3.98	18.62	29	قِيادَة	2,215	0.80	63.02
5	تَحْسِين	9,598	3.45	22.07	30	تَمَتَّع	2,197	0.79	63.81
6	دَعْم	9,549	3.43	25.50	31	عَزَّز	2,173	0.78	64.59
7	قُدْرَة	8,741	3.14	28.64	32	ثِقَة	2,127	0.76	65.36
8	ضَمان	8,731	3.14	31.77	33	رَغْم مِن	2,060	0.74	66.10
9	أَعْلَى	6,739	2.42	34.19	34	عَلَى رَغْم	2,017	0.72	66.82
10	كَفاءَة	6,478	2.33	36.52	35	إِيجابِيّ	1,982	0.71	67.53
11	فَعّالِيَّة	6,250	2.24	38.76	36	تَجاوَز	1,981	0.71	68.25
12	حَلّ	5,603	2.01	40.78	37	أَكَّد	1,872	0.67	68.92
13	أَفْضَل	5,517	1.98	42.76	38	ضَمِن	1,858	0.67	69.59
14	فُرْصَة	5,192	1.86	44.62	39	شَفّافِيَّة	1,789	0.64	70.23
15	قُوَّة	5,097	1.83	46.45	40	شَكْل كَبِير	1,732	0.62	70.85
16	رائِد	4,466	1.60	48.06	41	مُنْتَظِم	1,726	0.62	71.47
17	تَقَدَّم	4,433	1.59	49.65	42	تَمَيُّز	1,705	0.61	72.08
18	نَجاح	4,095	1.47	51.12	43	مُتَمَيِّز	1,665	0.60	72.68
19	قَوِيّ	3,878	1.39	52.51	44	أَقْصَى	1,639	0.59	73.27
20	حَقَّق	3,683	1.32	53.84	45	جَيِّد	1,589	0.57	73.84
21	تَعاوُن	3,670	1.32	55.16	46	جائِزَة	1,557	0.56	74.40
22	فَعّال	3,465	1.24	56.40	47	تَقَدُّم	1,542	0.55	74.95
23	إِنْجاز	3,067	1.10	57.50	48	شارَك	1,497	0.54	75.49
24	تَمْكِين	2,787	1.00	58.50	49	تَطَوُّر	1,489	0.53	76.03
25	ٱِبْتِكار	2,714	0.97	59.48	50	شَكْل مُسْتَمِرّ	1,434	0.52	76.54
All							274,791		

This table presents the most frequent positive sentiment words identified in the machine-translated Arabic annual reports (from English). The translated Arabic annual reports were established by relying on the Google Cloud Translation API. The occurrences of Arabic words were computed using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Frequencies and cumulative percentages reflect lemma/token-level matches.

Table C.9 (b-1) Most Frequent Negative Sentiment Words Occurring in the Translated-Arabic Annual Reports

Rank					Rank				
	Word	Total	%	Cum %		Word	Total	%	Cum %
1	خَسارَة	7,355	5.74	5.74	26	عُقُوبَة	1,055	0.82	41.14
2	ٱنْخِفاض	4,431	3.46	9.20	27	خَطَأ	1,046	0.82	41.95
3	تَعْوِيض	3,872	3.02	12.22	28	إِغْلاق	1,029	0.80	42.76
4	تَقْلِيل	3,319	2.59	14.81	29	ٱسْتِبْدال	956	0.75	43.50
5	تَحَدِّي	3,079	2.40	17.22	30	تَحَمَّل	937	0.73	44.24
6	ٱعْتِراف	2,637	2.06	19.27	31	أَزْمَة	917	0.72	44.95
7	تَخْفِيف	2,243	1.75	21.03	32	ضَرَر	900	0.70	45.65
8	خَضَع	1,992	1.55	22.58	33	أَدان	894	0.70	46.35
9	سَلْبِيّ	1,922	1.50	24.08	34	خِلاف	867	0.68	47.03
10	ٱنْخِفاض قِيمَة	1,523	1.19	25.27	35	ٱحْتِيال	867	0.68	47.71
11	بالِغ	1,498	1.17	26.44	36	عَدَم قُدْرَة	857	0.67	48.37
12	تَسْوِيَة	1,493	1.17	27.60	37	فَشَل	850	0.66	49.04
13	ضُعْف	1,445	1.13	28.73	38	مُخالَفَة	829	0.65	49.68
14	غَطّى	1,433	1.12	29.85	39	مَوْقِف	825	0.64	50.33
15	حادِث	1,369	1.07	30.92	40	تَحَوُّط	823	0.64	50.97
16	إِلْغاء	1,287	1.00	31.92	41	مُطالَبَة	803	0.63	51.60
17	تَخْفِيض	1,275	1.00	32.92	42	ضَرُورِيّ	800	0.62	52.22
18	تَنازُل	1,270	0.99	33.91	43	مَنْع	758	0.59	52.81
19	تَضارُب	1,228	0.96	34.87	44	فَصْل	740	0.58	53.39
20	ٱسْتِفْسار	1,214	0.95	35.82	45	مُشْكِلَة	721	0.56	53.95
21	مُواجَهَة	1,210	0.94	36.76	46	فَرَض	716	0.56	54.51
22	حَمَل	1,210	0.94	37.71	47	تَعارَض	701	0.55	55.06
23	ضِدّ	1,142	0.89	38.60	48	مُعْتَرَف	690	0.54	55.60
24	خَفْض	1,135	0.89	39.48	49	صُعُوبَة	680	0.53	56.13
25	ٱنْخَفَض	1,066	0.83	40.31	50	ٱحْتاج	670	0.52	56.65
All							140,272		

This table presents the most frequent negative sentiment words identified in the machine-translated Arabic annual reports (from English). The translated Arabic annual reports were established by relying on the Google Cloud Translation API. The occurrences of Arabic words were computed using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Frequencies and cumulative percentages reflect lemma/token-level matches.

Table C.9 (c-1) Most Frequent Uncertain Sentiment Words Occurring in the Translated-Arabic Annual Reports

Rank					Rank				
	Word	Total	%	Cum %		Word	Total	%	Cum %
1	مَخاطِر	44,300	51.22	51.22	26	راجَع	437	0.51	92.76
2	مُتَوَقَّع	4,913	5.68	56.90	27	تَقْرِيب	420	0.49	93.24
3	قَدَّر	3,070	3.55	60.45	28	تَراوَح	400	0.46	93.71
4	مُحْتَمَل	2,843	3.29	63.74	29	ٱِفْتِراضِيّ	382	0.44	94.15
5	مُقْتَرَح	2,761	3.19	66.93	30	ٱِقْتَرَح	376	0.43	94.58
6	تَعَرَّض	2,593	3.00	69.93	31	مُرَجِّح	330	0.38	94.96
7	تَوَقُّع	2,304	2.66	72.60	32	تَنَبُّؤ	328	0.38	95.34
8	مَعْقُول	1,693	1.96	74.55	33	غَيْر مَلْمُوس	282	0.33	95.67
9	مُتَغَيِّر	1,648	1.91	76.46	34	مِن مُحْتَمَل	253	0.29	95.96
10	أَظْهَر	1,297	1.50	77.96	35	تَغَيَّر	237	0.27	96.24
11	تَوَقَّع	1,196	1.38	79.34	36	وِقايَة	215	0.25	96.48
12	حِوال	1,180	1.36	80.71	37	مِن مُرَجِّح	191	0.22	96.70
13	إِمْكانِيَّة	1,142	1.32	82.03	38	مُتَحَفِّظ	169	0.20	96.90
14	ٱِفْتِراض	1,033	1.19	83.22	39	تَقَلَّب	161	0.19	97.09
15	تَوْضِيح	986	1.14	84.36	40	مُعْتاد	139	0.16	97.25
16	تَعْلِيق	908	1.05	85.41	41	مُتَفاوِت	131	0.15	97.40
17	ٱِعْتَقَد	890	1.03	86.44	42	نادِر	123	0.14	97.54
18	ٱِحْتِمال	866	1.00	87.44	43	مُمْكِن أَنَّ	113	0.13	97.67
19	قارَب	746	0.86	88.31	44	مَشْرُوط	113	0.13	97.80
20	إِيضاح	668	0.77	89.08	45	غَيْر مَضْمُون	108	0.12	97.93
21	تَحَفُّظ	637	0.74	89.81	46	بَدا	107	0.12	98.05
22	مُؤَقَّت	632	0.73	90.54	47	مُفْتَرَض	98	0.11	98.16
23	مَبْدَئِيّ	515	0.60	91.14	48	إِعادَة نَظَر	90	0.10	98.27
24	عَدَم يَقِين	503	0.58	91.72	49	تَحَسُّب	84	0.10	98.36
25	ما قَرُب	458	0.53	92.25	50	ٱِقْتَرَب	77	0.09	98.45
All							104,001		

This table presents the most frequent uncertain sentiment words identified in the machine-translated Arabic annual reports (from English). The translated Arabic annual reports were established by relying on the Google Cloud Translation API. The occurrences of Arabic words were computed using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Frequencies and cumulative percentages reflect lemma/token-level matches.

Appendix C.10 - Translated-English Annual Reports

Table C.10 (a-1) Most Frequent Positive Sentiment Words Occurring in the Translated-English Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	achieve	8,452	6.02	6.02	26	transparency	1,774	1.26	63.76
2	achieving	6,256	4.45	10.47	27	improvement	1,713	1.22	64.98
3	best	6,055	4.31	14.78	28	reward	1,665	1.18	66.16
4	efficiency	5,511	3.92	18.70	29	good	1,521	1.08	67.24
5	enhance	5,173	3.68	22.38	30	succeeded	1,309	0.93	68.17
6	opportunities	4,444	3.16	25.54	31	strengthening	1,291	0.92	69.09
7	achieved	4,440	3.16	28.70	32	satisfaction	1,146	0.82	69.91
8	strong	4,099	2.92	31.62	33	better	1,089	0.78	70.68
9	improve	3,769	2.68	34.30	34	successful	1,068	0.76	71.44
10	enhancing	3,637	2.59	36.89	35	improved	1,055	0.75	72.19
11	leading	3,432	2.44	39.33	36	enables	1,050	0.75	72.94
12	success	3,427	2.44	41.77	37	strengthen	1,047	0.75	73.69
13	improving	3,391	2.41	44.18	38	pleased	1,037	0.74	74.42
14	leadership	3,060	2.18	46.36	39	exceptional	1,032	0.73	75.16
15	highest	2,791	1.99	48.35	40	achievement	1,023	0.73	75.89
16	achievements	2,344	1.67	50.02	41	opportunity	981	0.70	76.59
17	innovation	2,266	1.61	51.63	42	strengths	948	0.67	77.26
18	positive	2,147	1.53	53.16	43	enabling	909	0.65	77.91
19	despite	2,025	1.44	54.60	44	strength	881	0.63	78.53
20	innovative	1,903	1.35	55.95	45	achieves	847	0.60	79.14
21	excellence	1,889	1.34	57.30	46	successfully	846	0.60	79.74
22	enable	1,846	1.31	58.61	47	advantage	793	0.56	80.30
23	profitability	1,844	1.31	59.92	48	improvements	731	0.52	80.82
24	integrity	1,837	1.31	61.23	49	charitable	726	0.52	81.34
25	progress	1,775	1.26	62.49	50	efficient	692	0.49	81.83
All							140,095		

This table presents the most frequent positive sentiment words identified in the machine-translated English annual reports (from Arabic). The translated English annual reports were generated using Google Cloud Translation API. The occurrences of English words were computed using the Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Table C.10 (b-1) Most Frequent Negative Sentiment Words Occurring in the Translated-English Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	loss	3,975	4.78	4.78	26	difficult	618	0.74	43.50
2	losses	3,641	4.38	9.16	27	cancellation	603	0.73	44.22
3	challenges	2,989	3.59	12.75	28	difficulties	599	0.72	44.94
4	conflict	2,237	2.69	15.44	29	adverse	569	0.68	45.63
5	claims	2,103	2.53	17.97	30	restructuring	568	0.68	46.31
6	exposed	2,009	2.42	20.38	31	penalty	524	0.63	46.94
7	against	1,856	2.23	22.62	32	conflicts	518	0.62	47.56
8	negative	1,621	1.95	24.57	33	confront	506	0.61	48.17
9	decline	1,473	1.77	26.34	34	laundering	495	0.60	48.76
10	impairment	1,378	1.66	27.99	35	unable	491	0.59	49.35
11	negatively	1,246	1.50	29.49	36	errors	485	0.58	49.94
12	failure	1,020	1.23	30.72	37	concern	475	0.57	50.51
13	weaknesses	1,003	1.21	31.92	38	overcome	464	0.56	51.07
14	concerned	960	1.15	33.08	39	problems	451	0.54	51.61
15	inability	829	1.00	34.08	40	lack	422	0.51	52.12
16	fraud	809	0.97	35.05	41	complaints	414	0.50	52.61
17	damage	795	0.96	36.00	42	harm	411	0.49	53.11
18	crisis	746	0.90	36.90	43	solvency	377	0.45	53.56
19	default	738	0.89	37.79	44	challenge	371	0.45	54.01
20	violations	738	0.89	38.68	45	questions	371	0.45	54.45
21	disclosed	737	0.89	39.56	46	accidents	369	0.44	54.90
22	absence	723	0.87	40.43	47	incidents	367	0.44	55.34
23	penalties	679	0.82	41.25	48	objection	361	0.43	55.77
24	dismissal	626	0.75	42.00	49	resignation	347	0.42	56.19
25	disclosing	626	0.75	42.75	50	closure	338	0.41	56.60
All							84,460		

This table presents the most frequent negative sentiment words identified in the machine-translated English annual reports (from Arabic). The translated English annual reports were generated using Google Cloud Translation API. The occurrences of English words were computed using the Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Table C.10 (c-1) Most Frequent Uncertain Sentiment Words Occurring in the Translated-English Annual Reports

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	risk	24,503	28.31	28.31	26	vary	249	0.29	93.21
2	risks	22,948	26.51	54.82	27	clarifications	248	0.29	93.50
3	may	15,519	17.93	72.75	28	clarification	243	0.28	93.78
4	possible	2,053	2.37	75.13	29	differ	239	0.28	94.05
5	exposure	1,780	2.06	77.18	30	predict	204	0.24	94.29
6	approximately	1,624	1.88	79.06	31	exposures	181	0.21	94.50
7	fluctuations	1,535	1.77	80.83	32	contingent	175	0.20	94.70
8	could	1,408	1.63	82.46	33	appear	169	0.20	94.89
9	precautionary	1,182	1.37	83.82	34	depending	169	0.20	95.09
10	believes	1,091	1.26	85.08	35	assume	166	0.19	95.28
11	possibility	784	0.91	85.99	36	assumed	164	0.19	95.47
12	depends	783	0.90	86.89	37	varying	161	0.19	95.66
13	assumptions	743	0.86	87.75	38	dependence	149	0.17	95.83
14	variable	581	0.67	88.42	39	nearly	132	0.15	95.98
15	believe	509	0.59	89.01	40	sudden	131	0.15	96.13
16	uncertainty	450	0.52	89.53	41	revised	130	0.15	96.28
17	preliminary	448	0.52	90.05	42	precautions	124	0.14	96.43
18	variables	435	0.50	90.55	43	probable	121	0.14	96.57
19	unusual	321	0.37	90.92	44	assuming	116	0.13	96.70
20	depend	314	0.36	91.29	45	anticipate	107	0.12	96.82
21	assumes	296	0.34	91.63	46	uncertain	101	0.12	96.94
22	probability	291	0.34	91.96	47	assumption	100	0.12	97.06
23	fluctuation	291	0.34	92.30	48	almost	96	0.11	97.17
24	fluctuate	270	0.31	92.61	49	pending	95	0.11	97.28
25	intangible	267	0.31	92.92	50	likelihood	91	0.11	97.38
All							89,376		

This table presents the most frequent uncertain sentiment words identified in the machine-translated English annual reports (from Arabic). The translated English annual reports were generated using Google Cloud Translation API. The occurrences of English words were computed using the Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Appendix C.11 - Translated-Arabic CEO Letters

Table C.11 (a-1) Most Frequent Positive Sentiment Words Occurring in the Translated Arabic CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	نُمُوّ	1,102	6.96	6.96	26	تَقَدُّم	162	1.02	61.26
2	تَحْقِيق	784	4.95	11.90	27	ضَمان	159	1.00	62.27
3	تَعْزِيز	689	4.35	16.25	28	قِيادَة	157	0.99	63.26
4	تَطْوِير	597	3.77	20.02	29	جائِزَة	153	0.97	64.22
5	دَعْم	575	3.63	23.65	30	تَمَيُّز	152	0.96	65.18
6	تَحْسِين	437	2.76	26.41	31	رَغْم مِن	148	0.93	66.12
7	نَجاح	426	2.69	29.10	32	عَلَى رَغْم	146	0.92	67.04
8	حَقَّق	424	2.68	31.77	33	تَعاوُن	142	0.90	67.94
9	فُرْصَة	381	2.40	34.18	34	تَمْكِين	138	0.87	68.81
10	قُوَّة	363	2.29	36.47	35	إِيجابِيّ	131	0.83	69.63
11	إِنْجاز	340	2.15	38.62	36	رِبْحِيّ	125	0.79	70.42
12	قُدْرَة	329	2.08	40.69	37	مُرُونَة	115	0.73	71.15
13	رائِد	327	2.06	42.76	38	ٱسْتِثْنائِيّ	112	0.71	71.86
14	أَفْضَل	319	2.01	44.77	39	ناجِح	104	0.66	72.51
15	قَوِيّ	282	1.78	46.55	40	تَطَوُّر	91	0.57	73.09
16	كَفاءَة	273	1.72	48.27	41	مُتَقَدِّم	90	0.57	73.65
17	حَلّ	251	1.58	49.86	42	تَجاوَز	87	0.55	74.20
18	ٱبْتِكار	249	1.57	51.43	43	مُتَطَوِّر	84	0.53	74.73
19	أَعْلَى	238	1.50	52.93	44	شَكْل كَبِير	84	0.53	75.26
20	تَقَدَّم	225	1.42	54.35	45	أَكَّد	82	0.52	75.78
21	ثِقَة	217	1.37	55.72	46	نَجَح	80	0.50	76.29
22	ٱسْتِفادَة	192	1.21	56.93	47	جَيِّد	80	0.50	76.79
23	وَلاء	182	1.15	58.08	48	أَسْعَد	79	0.50	77.29
24	عَزَّز	174	1.10	59.18	49	تَحَسُّن	77	0.49	77.78
25	مُتَمَيِّز	168	1.06	60.24	50	فَعّال	76	0.48	78.26
All							15,746		

This table presents the most frequent positive sentiment words identified in the machine-translated Arabic CEO letters (from English). The translated Arabic CEO letters were generated using the Google Cloud Translation API. The occurrences of Arabic words were computed using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Frequencies and cumulative percentages reflect lemma/token-level matches.

Table C.11 (b-1) Most Frequent Negative Sentiment Words Occurring in the Translated Arabic CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	تَحَدِّي	304	11.48	11.48	26	شِدَّة	24	0.91	55.74
2	اِنْخِفاض	117	4.42	15.90	27	ضَرُورِيّ	23	0.87	56.61
3	خَسارَة	104	3.93	19.83	28	غَطّى	22	0.83	57.44
4	مُواجَهَة	74	2.79	22.62	29	تَخْفِيض	20	0.76	58.19
5	تَقْلِيل	71	2.68	25.30	30	مُؤَخَّر	20	0.76	58.95
6	بالِغ	68	2.57	27.87	31	عَقَبَة	19	0.72	59.67
7	صَعْب	66	2.49	30.36	32	تَرْشِيد	19	0.72	60.39
8	إِغْلاق	57	2.15	32.52	33	مُعاكِس	19	0.72	61.10
9	خَفْض	52	1.96	34.48	34	أَنْهَى	18	0.68	61.78
10	تَخْفِيف	50	1.89	36.37	35	صارِم	17	0.64	62.42
11	أَزْمَة	48	1.81	38.18	36	اِحْتاج	17	0.64	63.07
12	اِنْخَفَض	47	1.77	39.95	37	مُعارِض	17	0.64	63.71
13	اِعْتِراف	36	1.36	41.31	38	قَطَع	17	0.64	64.35
14	حَرَم	36	1.36	42.67	39	مُنْخَفِض	16	0.60	64.95
15	إِعادَة هَيْكَلَة	35	1.32	44.00	40	مُنافِس	16	0.60	65.56
16	جادّ	33	1.25	45.24	41	صُعُوبَة	16	0.60	66.16
17	لَوْم	33	1.25	46.49	42	آل	16	0.60	66.77
18	سَلْبِيّ	31	1.17	47.66	43	اِسْتِغْلال	16	0.60	67.37
19	فَرَض	30	1.13	48.79	44	حادِث	14	0.53	67.90
20	تَداعِي	30	1.13	49.92	45	اِنْقِطاع	14	0.53	68.43
21	مِحْوَرِيّ	29	1.10	51.02	46	خَضَع	14	0.53	68.96
22	تَعْوِيض	26	0.98	52.00	47	ضِدّ	14	0.53	69.49
23	حَجْز	25	0.94	52.95	48	مُضْطَرِب	13	0.49	69.98
24	حَمَل	25	0.94	53.89	49	حَظْر	13	0.49	70.47
25	مَوْقِف	25	0.94	54.83	50	عانَى	13	0.49	70.96
All							2,793		

This table presents the most frequent negative sentiment words identified in the machine-translated Arabic CEO letters (from English). The translated Arabic CEO letters were generated using the Google Cloud Translation API. The occurrences of Arabic words were computed using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Frequencies and cumulative percentages reflect lemma/token-level matches.

Table C.11 (c-1) Most Frequent Uncertain Sentiment Words Occurring in the Translated Arabic CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	مَخاطِر	104	10.98	10.98	26	وِقايَة	7	0.74	90.18
2	قَدَّر	103	10.88	21.86	27	قارَب	6	0.63	90.81
3	أَظْهَر	83	8.76	30.62	28	تَغَيَّر	6	0.63	91.45
4	مُتَوَقَّع	73	7.71	38.33	29	اِعْتِقاد	6	0.63	92.08
5	تَوَقَّع	70	7.39	45.72	30	اِفْتِراض	5	0.53	92.61
6	تَوَقُّع	66	6.97	52.69	31	اِقْتَرَح	5	0.53	93.14
7	مُتَغَيِّر	47	4.96	57.66	32	مُعْتَمَد عَلَى	4	0.42	93.56
8	اِعْتَقَد	38	4.01	61.67	33	مُعْتاد	4	0.42	93.98
9	مُحْتَمَل	35	3.70	65.36	34	تَعْلِيق	4	0.42	94.40
10	ما قَرُب	32	3.38	68.74	35	مُتَحَفِّظ	4	0.42	94.83
11	إِمْكانِيَّة	30	3.17	71.91	36	إِلَى حَدّ ما	4	0.42	95.25
12	حِوال	28	2.96	74.87	37	راجَع	3	0.32	95.56
13	عَدَم يَقِين	16	1.69	76.56	38	مُنْعَطَف	3	0.32	95.88
14	اِفْتِراضِيّ	15	1.58	78.14	39	نادِر	3	0.32	96.20
15	تَقْرِيب	14	1.48	79.62	40	مِن مُرَجَّح	3	0.32	96.52
16	اِنْتَظَر	12	1.27	80.89	41	أَوْحَى	3	0.32	96.83
17	تَراوَح	11	1.16	82.05	42	بَدا	3	0.32	97.15
18	مَعْقُول	10	1.06	83.10	43	مُضارِب	2	0.21	97.36
19	مُؤَقَّت	10	1.06	84.16	44	تَحَسُّب	2	0.21	97.57
20	تَنَبُّؤ	9	0.95	85.11	45	إِعادَة دِراسَة	2	0.21	97.78
21	مُقْتَرَح	9	0.95	86.06	46	تَرَقَّب	2	0.21	97.99
22	تَعَرَّض	9	0.95	87.01	47	غَيْر مُؤَكَّد	2	0.21	98.20
23	رُبَّما	8	0.84	87.86	48	لَعَلَّ	1	0.11	98.31
24	اِقْتَرَب	8	0.84	88.70	49	قُدْرَة عَلَى تَنَبُّؤ	1	0.11	98.42
25	اِحْتِمال	7	0.74	89.44	50	غَيْر واضِح	1	0.11	98.52
All							1,136		

This table presents the most frequent uncertain sentiment words identified in the machine-translated Arabic CEO letters (from English). The translated Arabic CEO letters were generated using the Google Cloud Translation API. The occurrences of Arabic words were computed using the Arabic Financial Sentiment Dictionary (ArFinSD). The Arabic words were extracted based on the lemmatized forms. Frequencies and cumulative percentages reflect lemma/token-level matches.

Appendix C.12 -Translated-English CEO Letters

Table C.12 (a-1) Most Frequent Positive Sentiment Words Occurring in the Translated-English CEO Letters

Rank					Rank				
	Word	Total	%	Cum %		Word	Total	%	Cum %
1	achieve	546	5.73	5.73	26	successful	101	1.06	67.82
2	achieving	469	4.92	10.66	27	successes	94	0.99	68.81
3	achieved	439	4.61	15.27	28	profitability	94	0.99	69.80
4	success	410	4.30	19.57	29	improvement	93	0.98	70.77
5	strong	330	3.46	23.03	30	pleased	93	0.98	71.75
6	best	328	3.44	26.48	31	strength	92	0.97	72.71
7	enhance	318	3.34	29.82	32	enable	92	0.97	73.68
8	opportunities	310	3.25	33.07	33	satisfaction	89	0.93	74.61
9	achievements	274	2.88	35.95	34	opportunity	82	0.86	75.48
10	efficiency	263	2.76	38.71	35	strengthen	81	0.85	76.33
11	enhancing	256	2.69	41.40	36	achievement	73	0.77	77.09
12	leading	239	2.51	43.91	37	better	71	0.75	77.84
13	leadership	228	2.39	46.30	38	strengthened	67	0.70	78.54
14	progress	197	2.07	48.37	39	confident	61	0.64	79.18
15	innovation	195	2.05	50.41	40	improved	56	0.59	79.77
16	despite	191	2.01	52.42	41	successfully	56	0.59	80.36
17	improving	175	1.84	54.26	42	enabling	54	0.57	80.92
18	excellence	175	1.84	56.09	43	enhanced	53	0.56	81.48
19	improve	168	1.76	57.86	44	advantage	53	0.56	82.04
20	highest	162	1.70	59.56	45	good	48	0.50	82.54
21	positive	155	1.63	61.19	46	enabled	44	0.46	83.00
22	innovative	154	1.62	62.80	47	valuable	42	0.44	83.44
23	exceptional	152	1.60	64.40	48	stable	41	0.43	83.87
24	strengthening	120	1.26	65.66	49	prosperity	39	0.41	84.28
25	succeeded	105	1.10	66.76	50	attractive	39	0.41	84.69
All							9,506		

This table presents the most frequent positive sentiment words identified in the machine-translated English CEO letters (from Arabic). The translated English CEO letters were generated using Google Cloud Translation API. The occurrences of English words were computed using the Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Table C.12 (b-1) Most Frequent Negative Sentiment Words Occurring in the Translated-English CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	challenges	321	21.33	21.33	26	seizing	10	0.66	66.25
2	overcome	64	4.25	25.58	27	poor	10	0.66	66.91
3	loss	58	3.85	29.44	28	postponing	9	0.60	67.51
4	difficult	56	3.72	33.16	29	concerns	9	0.60	68.11
5	decline	46	3.06	36.21	30	disruptions	9	0.60	68.70
6	losses	42	2.79	39.00	31	disruption	9	0.60	69.30
7	crisis	36	2.39	41.40	32	unfavorable	8	0.53	69.83
8	difficulties	33	2.19	43.59	33	crises	8	0.53	70.37
9	restructuring	33	2.19	45.78	34	miss	8	0.53	70.90
10	negative	31	2.06	47.84	35	restructure	8	0.53	71.43
11	seize	29	1.93	49.77	36	exploiting	8	0.53	71.96
12	obstacles	26	1.73	51.50	37	problems	7	0.47	72.43
13	confront	24	1.59	53.09	38	solvency	7	0.47	72.89
14	closure	24	1.59	54.68	39	suspension	7	0.47	73.36
15	claims	23	1.53	56.21	40	turmoil	7	0.47	73.82
16	challenge	23	1.53	57.74	41	negatively	7	0.47	74.29
17	against	18	1.20	58.94	42	complaints	7	0.47	74.75
18	overcoming	16	1.06	60.00	43	confronting	7	0.47	75.22
19	concerned	14	0.93	60.93	44	threats	7	0.47	75.68
20	serious	13	0.86	61.79	45	restructured	6	0.40	76.08
21	declined	12	0.80	62.59	46	rationalize	6	0.40	76.48
22	easing	12	0.80	63.39	47	suffering	6	0.40	76.88
23	challenging	11	0.73	64.12	48	forced	6	0.40	77.28
24	rationalizing	11	0.73	64.85	49	severe	6	0.40	77.67
25	rationalization	11	0.73	65.58	50	urgent	5	0.33	78.01
All							1,543		

This table presents the most frequent negative sentiment words identified in the machine-translated English CEO letters (from Arabic). The translated English CEO letters were generated using Google Cloud Translation API. The occurrences of English words were computed using the Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Table C.12 (c-1) Most Frequent Uncertain Sentiment Words Occurring in the Translated-English CEO Letters

Rank	Word	Total	%	Cum %	Rank	Word	Total	%	Cum %
1	may	123	19.10	19.10	26	somewhat	4	0.62	90.68
2	risk	69	10.71	29.81	27	possibilities	4	0.62	91.30
3	possible	68	10.56	40.37	28	exposure	4	0.62	91.93
4	approximately	48	7.45	47.83	29	anticipation	3	0.47	92.39
5	risks	40	6.21	54.04	30	suggests	3	0.47	92.86
6	believe	33	5.12	59.16	31	predictive	3	0.47	93.32
7	precautionary	29	4.50	63.66	32	unusual	3	0.47	93.79
8	believes	20	3.11	66.77	33	varied	3	0.47	94.25
9	nearly	19	2.95	69.72	34	predicted	2	0.31	94.57
10	fluctuations	19	2.95	72.67	35	preliminary	2	0.31	94.88
11	uncertainty	13	2.02	74.69	36	cautious	2	0.31	95.19
12	possibility	11	1.71	76.40	37	revised	2	0.31	95.50
13	could	10	1.55	77.95	38	sometimes	2	0.31	95.81
14	anticipate	8	1.24	79.19	39	variable	2	0.31	96.12
15	assume	8	1.24	80.43	40	varying	2	0.31	96.43
16	believing	7	1.09	81.52	41	depending	2	0.31	96.74
17	almost	7	1.09	82.61	42	assuming	2	0.31	97.05
18	perhaps	7	1.09	83.70	43	predict	1	0.16	97.20
19	dependence	7	1.09	84.78	44	pending	1	0.16	97.36
20	sudden	6	0.93	85.71	45	unclear	1	0.16	97.52
21	depend	6	0.93	86.65	46	uncertain	1	0.16	97.67
22	depends	6	0.93	87.58	47	unfamiliar	1	0.16	97.83
23	variables	6	0.93	88.51	48	reconsider	1	0.16	97.98
24	appeared	5	0.78	89.29	49	reconsidering	1	0.16	98.14
25	appear	5	0.78	90.06	50	unknown	1	0.16	98.29
All							697		

This table presents the most frequent uncertain sentiment words identified in the machine-translated English CEO letters (from Arabic). The translated English CEO letters were generated using Google Cloud Translation API. The occurrences of English words were computed using the Loughran and McDonald (LM) Dictionary. The English words were extracted based on their surface forms.

Appendix C.13 - Translation Assessment Results for Arabic and English CEO Letters

Table C.13 (a-1) Original vs Machine-Translated CEO Letters Textual Sentiment Analysis

	Original CEO letters					Machine-translated CEO letters					Pairwise Corr.	Spearman Corr.	ICC [3,2]
	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)	Mean (%)	Median (%)	SD (%)	Min (%)	Max (%)			
Panel A: Arabic language; N=274													
POS	10.45	10.75	2.87	2.91	20.76	10.73	10.61	2.98	3.73	20.15	0.853***	0.850***	0.920***
NEG	1.79	1.54	1.31	0	7.05	1.94	1.58	1.44	0	7.59	0.880***	0.865***	0.934***
UNC	0.68	0.60	0.54	0	2.72	0.73	0.64	0.56	0	2.92	0.753***	0.774***	0.859***
Panel B: English language; N=274													
POS	6.52	6.32	2.24	1.60	15.44	7.16	7.11	2.17	2.14	13.68	0.823***	0.806***	0.903***
NEG	1.28	0.88	1.25	0	9.30	1.24	0.96	1.40	0	6.89	0.862***	0.877***	0.923***
UNC	0.47	0.41	0.45	0	2.39	0.53	0.46	0.47	0	2.87	0.665***	0.676***	0.798***

The table shows summary statistics of the share of sentiment words in the original and machine-translated CEO letters. The Arabic language CEO letters classification is based on the Arabic Financial Sentiment Dictionary (ArFinSD), while the English language CEO letters are classified based on Loughran and McDonald's (2011) dictionary (LM dictionary). Additionally, this table displays simple pairwise correlations, Spearman rank correlations, and intraclass correlation (ICC) after Shrout and Fleiss (1979) between the CEO letters and their translated versions within the same language. These correlations relate to negative, positive, and uncertain word lists identified based on the LM dictionary and the Arabic financial dictionary. ***, **, and * reflect statistical significance at the 1%, 5%, and 10% levels, respectively.

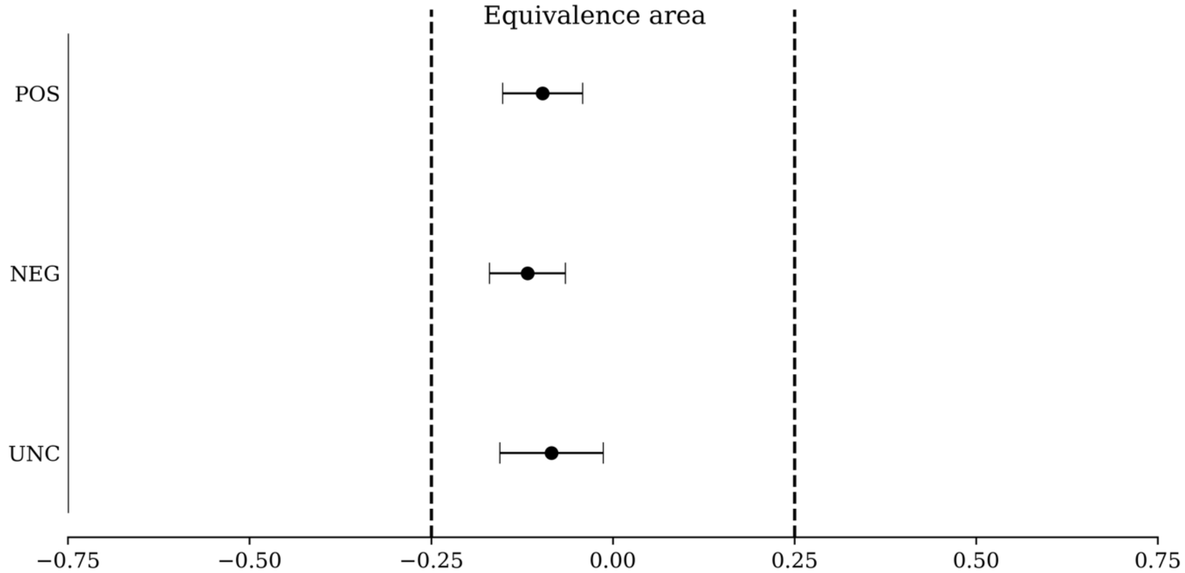


Figure C.13 (a-2) Two-sided equivalence test after Blair and Cole (2002). The figure shows the equivalence test for the sentiment proportions between the original CEO letters and their Arabic translations of the corresponding English versions. The area of equivalence is defined as ± 0.25 standard deviations around zero between the original Arabic CEO letters and translated versions for each sentiment category, with the horizontal bars reflecting the 90% confidence intervals.

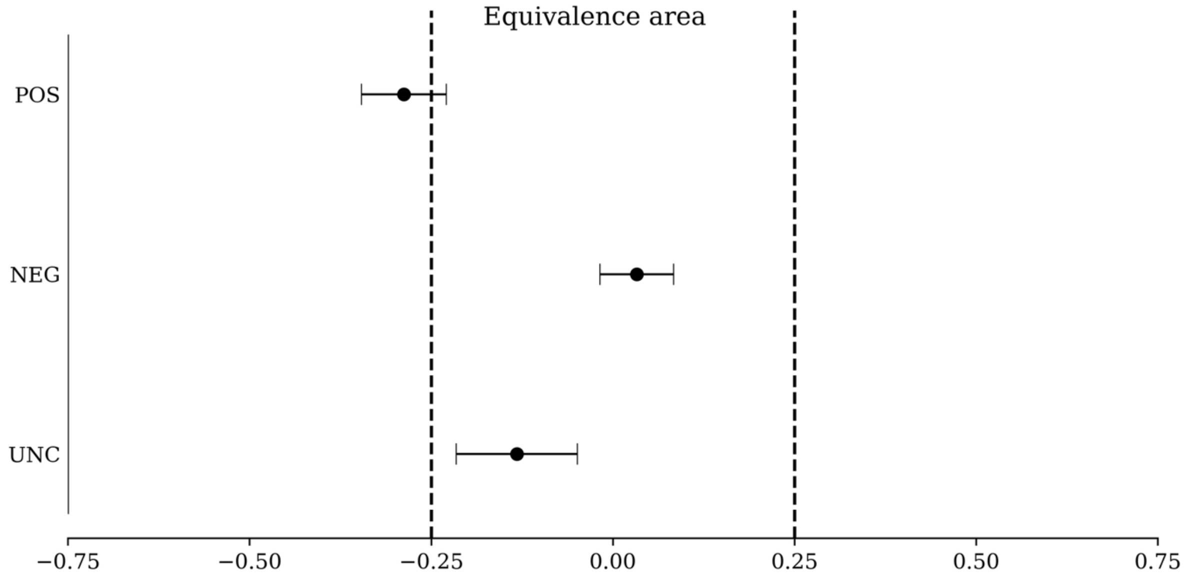


Figure C.13 (a-3) Two-sided equivalence test after Blair and Cole (2002). The figure illustrates the equivalence test for the sentiment proportions between the original CEO letters and their English translations of the corresponding Arabic versions. The area of equivalence is defined as ± 0.25 standard deviations around zero between the original English CEO letters and translated versions for each sentiment category, with the horizontal bars reflecting the 90% confidence intervals.

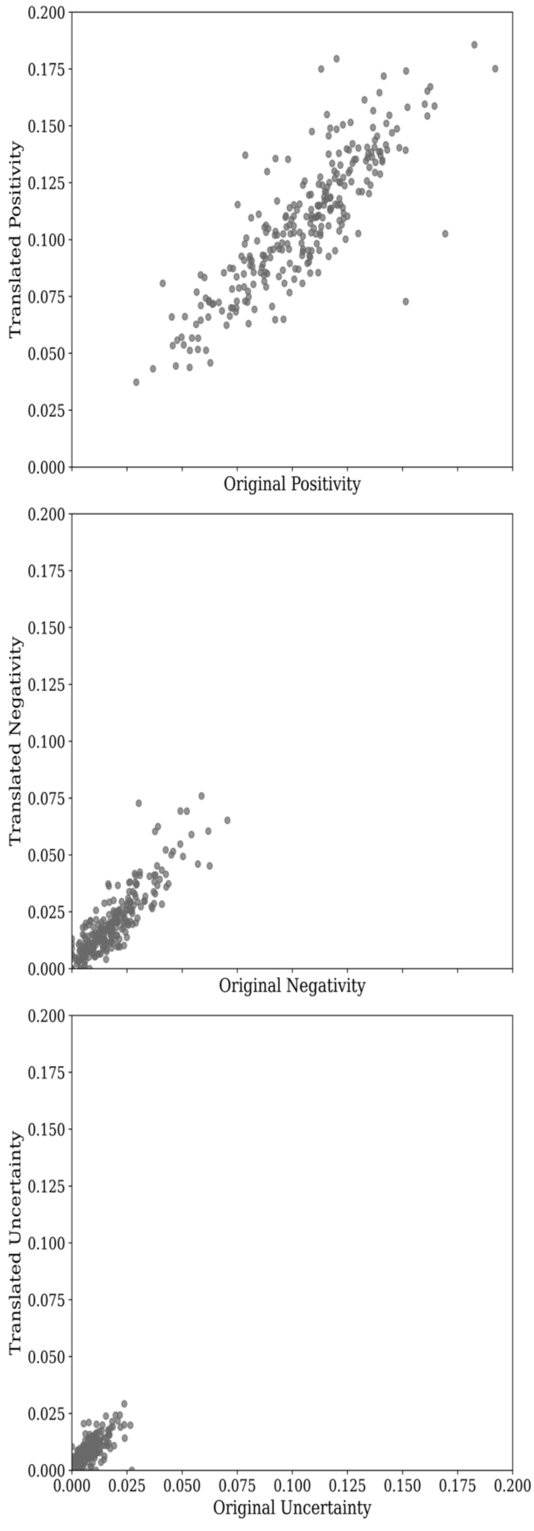


Figure C.13 (a-4) Scatter plots displaying the relationship between original and translated sentiment proportions for Positivity, Negativity, and Uncertainty in Arabic CEO letters.

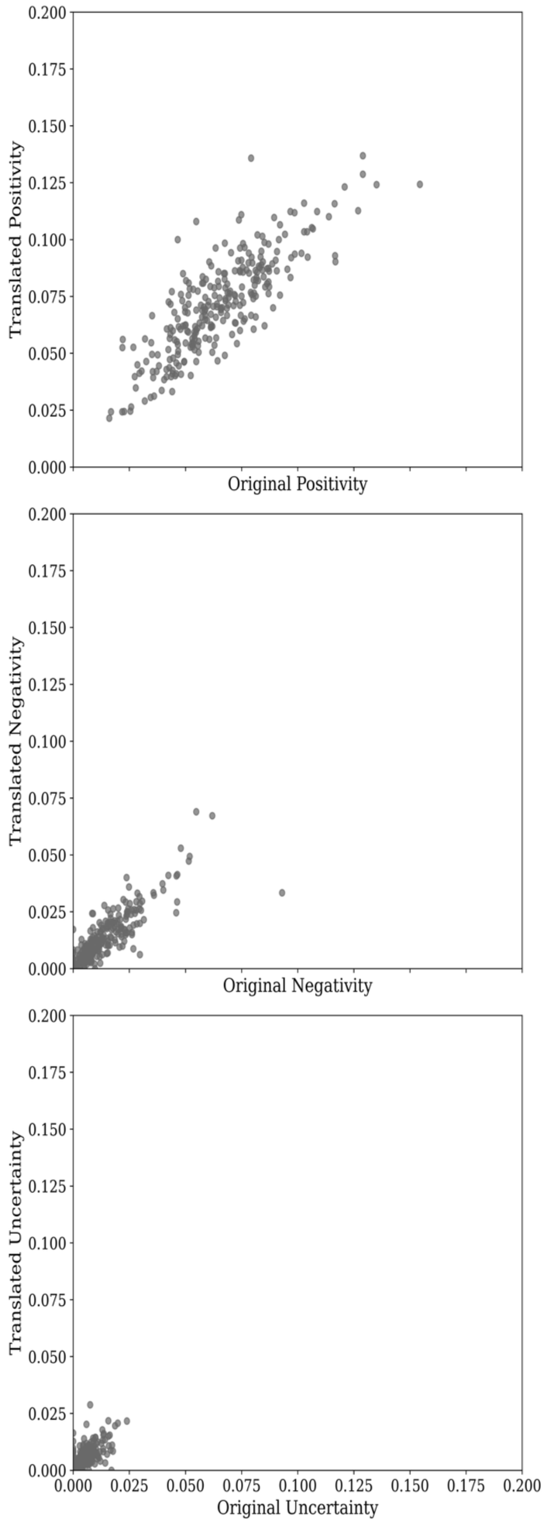
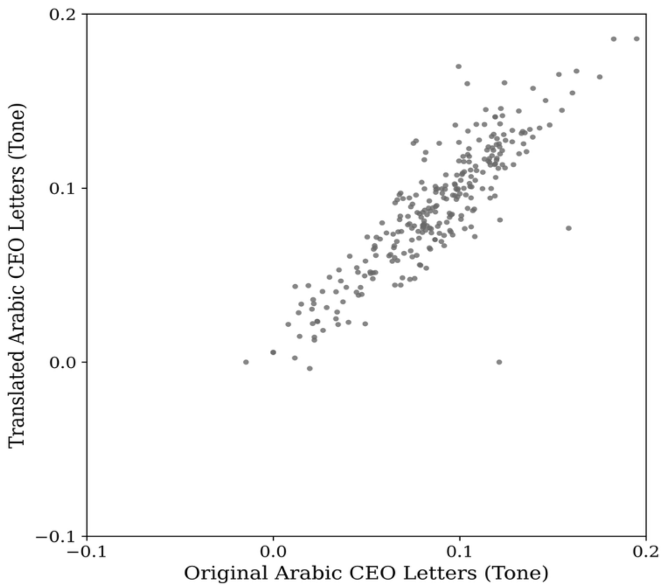
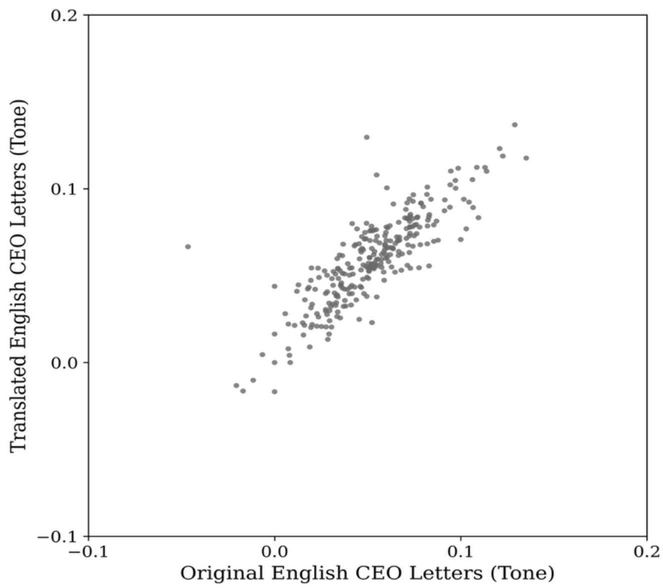


Figure C.13 (a-5) Scatter plots displaying the relationship between original and translated sentiment proportions for Positivity, Negativity, and Uncertainty in English CEO letters.



C.13 (a-6) The scatter plots display the overall sentiment (*Tone*) in the Arabic CEO letters and their machine-translated Arabic counterparts. The overall tone is obtained by subtracting the number of negative words from the number of positive words, normalized by the total number of words in the CEO letters.



C.13 (a-7) The scatter plots display the overall sentiment (*Tone*) in the English CEO letters and their machine-translated English counterparts. The overall tone is obtained by subtracting the number of negative words from the number of positive words, normalized by the total number of words in the CEO letters.

Chapter 6 - Appendix D

Table D.1 Variable Definition and Source		
Variable	Definition & Calculation	Source
CAR [-1,+t]	Cumulative abnormal return from day −1 to +t relative to filing date (market-adjusted abnormal returns).	Tadawul, computed
Size	Market cap = Shares outstanding × share Price Winsorized at 1st/99th percentiles; natural log-transformed	Bloomberg
Book-to-Market (B/M)	Book value of equity ÷ Market value of equity. Winsorized at 1st/99th percentiles; natural log-transformed	Bloomberg & computed
Share Turnover	Annual trading volume (shares traded) ÷ Shares outstanding. Winsorized at 1st/99th percentiles; natural log-transformed	Tadawul, Bloomberg, computed
Free-float Inst. Own	Percentage of free-float shares held by institutional investors ÷ 100. Winsorized at 1st/99th percentiles	Bloomberg, computed
Ar.Pos.	The share of positive words in Arabic annual report ÷ total words, excluding stop words.	ArFinSD
Ar.Neg.	The share of negative words in Arabic annual report ÷ total words, excluding stop words.	ArFinSD
Ar.Unc.	The share of uncertain words in Arabic annual report ÷ total words, excluding stop words.	ArFinSD
En.Pos.	The share of positive words in English annual report ÷ total words, excluding stop words.	LM
En.Neg.	The share of negative words in English annual report ÷ total words, excluding stop words.	LM
En.Unc.	The share of uncertain words in English annual report ÷ total words, excluding stop words.	LM

Appendix D.2 Regression Results

The appendix presents the complete regression results obtained for all event windows under study (CAR [-1, +1], CAR [-1, +5], and CAR [-1, +10]). Each table summarizes coefficient estimates and standard errors for a specific sentiment measure (positive and uncertainty), reported separately for the Arabic and English annual reports. All regressions employ a consistent model specification. Four firm-level variables are used as controls: the log of market capitalization (size), the log book-to-market ratio (B/M), the log of share turnover (Turnover), and free-float shares of institutional ownership (Free-float Inst. Own). Year and industry fixed effects are included in all regressions, with standard errors clustered at the firm level. Each event-window regression is estimated on a consistent sample of 686 firm-year observations. Each table is structured by language (a: Arabic; b: English) and sentiment category.

Table D.2 (a-1) Cumulative Abnormal Return

Explanatory variables	CAR [−1,+1]	CAR [−1,+5]	CAR [−1,+10]
Ar.Pos.	0.024 (0.085)	-0.123 (0.141)	-0.148 (0.184)
Log (Size)	0.003 (0.003)	0.005 (0.004)	-0.001 (0.005)
Log (B/M)	0.007*** (0.003)	0.01** (0.004)	0.012** (0.005)
Log (Turnover)	-0.001 (0.003)	0.0 (0.004)	-0.005 (0.005)
Free-float Inst. Own	-0.007 (0.015)	0.013 (0.028)	-0.008 (0.038)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	686	686	686
R-squared	0.089	0.096	0.109

The table presents results from event study regressions in which the dependent variable is cumulative abnormal returns (CAR) and the key explanatory variable is positive sentiment in Arabic annual reports. The table reports results for Arabic-language sentiment extracted using the ArFinSD dictionary. Standard errors (reported in parentheses) are clustered at the firm level. Significance levels are denoted as *** (1%), ** (5%), and * (10%). Control variables include the log of market capitalization, the log of book-to-market ratio, the log of share turnover, and free-float shares of institutional ownership. All regressions include year and industry fixed effects. Sample: 686 annual report filings from Saudi-listed firms, 2018-2023. Abnormal returns are calculated using the market-adjusted model.

Table D.2 (a-2) Cumulative Abnormal Return

Explanatory variables	CAR [−1,+1]	CAR [−1,+5]	CAR [−1,+10]
Ar.Unc.	-0.062 (0.2)	0.023 (0.315)	0.298 (0.395)
Log (Size)	0.003 (0.002)	0.004 (0.003)	-0.002 (0.004)
Log (B/M)	0.007*** (0.003)	0.009** (0.004)	0.012** (0.005)
Log (Turnover)	-0.001 (0.003)	-0.0 (0.004)	-0.006 (0.005)
Free-float Inst. Own	-0.007 (0.015)	0.012 (0.028)	-0.008 (0.038)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	686	686	686
R-squared	0.089	0.095	0.108

The table presents results from event study regressions in which the dependent variable is cumulative abnormal returns (CAR) and the key explanatory variable is uncertainty sentiment in Arabic annual reports. The table reports results for Arabic-language sentiment extracted using the ArFinSD dictionary. Standard errors (reported in parentheses) are clustered at the firm level. Significance levels are denoted as *** (1%), ** (5%), and * (10%). Control variables include the log of market capitalization, the log of book-to-market ratio, the log of share turnover, and free-float shares of institutional ownership. All regressions include year and industry fixed effects. Sample: 686 annual report filings from Saudi-listed firms, 2018-2023. Abnormal returns are calculated using the market-adjusted model.

Table D. 2 (b-1) Cumulative Abnormal Return

Explanatory variables	CAR [−1,+1]	CAR [−1,+5]	CAR [−1,+10]
En.Pos.	0.102 (0.15)	-0.264 (0.235)	-0.408 (0.315)
Log (Size)	0.002 (0.003)	0.005 (0.004)	-0.0 (0.005)
Log (B/M)	0.007** (0.003)	0.01** (0.004)	0.012** (0.005)
Log (Turnover)	-0.001 (0.003)	0.0 (0.004)	-0.005 (0.005)
Free-float Inst. Own	-0.008 (0.015)	0.014 (0.028)	-0.006 (0.039)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	686	686	686
R-squared	0.089	0.097	0.11

The table presents results from event study regressions in which the dependent variable is cumulative abnormal returns (CAR) and the key explanatory variable is positive sentiment in English annual reports. The table reports results for English-language sentiment extracted using the Loughran and McDonald (2011) dictionary. Standard errors (reported in parentheses) are clustered at the firm level. Significance levels are denoted as *** (1%), ** (5%), and * (10%). Control variables include the log of market capitalization, the log of book-to-market ratio, the log of share turnover, and free-float shares of institutional ownership. All regressions include year and industry fixed effects. Sample: 686 annual report filings from Saudi-listed firms, 2018-2023. Abnormal returns are calculated using the market-adjusted model.

Table D. 2 (b-2) Cumulative Abnormal Return

Explanatory variables	CAR [−1,+1]	CAR [−1,+5]	CAR [−1,+10]
En.Unc.	0.024 (0.151)	0.136 (0.24)	0.329 (0.308)
Log (Size)	0.003 (0.002)	0.004 (0.003)	-0.002 (0.004)
Log (B/M)	0.007*** (0.003)	0.009** (0.004)	0.012** (0.005)
Log (Turnover)	-0.001 (0.003)	-0.0 (0.004)	-0.006 (0.005)
Free-float Inst. Own	-0.007 (0.015)	0.013 (0.028)	-0.008 (0.038)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	686	686	686
R-squared	0.089	0.096	0.109

The table presents results from event study regressions in which the dependent variable is cumulative abnormal returns (CAR) and the key explanatory variable is uncertainty sentiment in English annual reports. The table reports results for English-language sentiment extracted using the Loughran and McDonald (2011) dictionary. Standard errors (reported in parentheses) are clustered at the firm level. Significance levels are denoted as *** (1%), ** (5%), and * (10%). Control variables include the log of market capitalization, the log of book-to-market ratio, the log of share turnover, and free-float shares of institutional ownership. All regressions include year and industry fixed effects. Sample: 686 annual report filings from Saudi-listed firms, 2018-2023. Abnormal returns are calculated using the market-adjusted model.

Appendix D.3 Extended-Window Regression Results

The appendix presents additional regression results for the extended event windows, CAR [-1, +15] and CAR [-1, +20], along with descriptive statistics for these CAR variables. Each table summarizes coefficient estimates and standard errors for a specific sentiment measure (positive, negative, and uncertainty), reported separately for the Arabic and English annual reports. All regressions employ a consistent model specification. Four firm-level variables are used as controls: the log of market capitalization (size), the log book-to-market ratio (B/M), the log of share turnover (Turnover), and free-float shares of institutional ownership (Free-float Inst. Own). Year and industry fixed effects are included in all regressions, with standard errors clustered at the firm level. Each event-window regression is estimated on a consistent sample of 686 firm-year observations. Each table is structured by language (a: Arabic; b: English) and sentiment category.

Table D.3 Descriptive Statistics for the Extended CAR Windows

Variables	Mean	SD	Min	50%	Max
Dependent variables (CAR)					
CAR [−1, +15]	-0.005	0.076	-0.356	-0.010	0.413
CAR [−1, +20]	-0.006	0.087	-0.352	-0.011	0.444

The table presents descriptive statistics for the cumulative abnormal return (CAR) variables used in the extended-window analysis. The CAR windows are measured from t-1 (relative to one day prior to the annual report release date) through t+15, and t+20 trading days. The sample comprises 686 firm-year observations for each variable. A list of variable definitions is provided in Appendix D.1.

Table D.3 (a-1) Cumulative Abnormal Return

Explanatory variables	CAR [−1,+15]	CAR [−1,+20]
Ar.Pos.	0.075 (0.212)	0.125 (0.240)
Log (Size)	-0.002 (0.005)	-0.005 (0.006)
Log (B/M)	0.016*** (0.005)	0.012* (0.006)
Log (Turnover)	-0.005 (0.005)	-0.009 (0.007)
Free-float Inst. Own	0.000 (0.047)	-0.010 (0.053)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	686	686
R-squared	0.113	0.144

The table presents results from event study regressions in which the dependent variable is cumulative abnormal returns (CAR) and the key explanatory variable is positive sentiment in Arabic annual reports. The regressions are reported for the extended event windows, CAR [−1,+15] and CAR [−1,+20]. The table reports results for Arabic-language sentiment extracted using the ArFinSD dictionary. Standard errors (reported in parentheses) are clustered at the firm level. Significance levels are denoted as *** (1%), ** (5%), and * (10%). Control variables include the log of market capitalization, the log of book-to-market ratio, the log of share turnover, and free-float shares of institutional ownership. All regressions include year and industry fixed effects. Sample: 686 annual report filings from Saudi-listed firms, 2018-2023. Abnormal returns are calculated using the market-adjusted model.

Table D.3 (a-2) Cumulative Abnormal Return

Explanatory variables	CAR [−1,+15]	CAR [−1,+20]
Ar.Unc.	0.017 (0.488)	-0.233 (0.544)
Log (Size)	-0.002 (0.005)	-0.005 (0.006)
Log (B/M)	0.016*** (0.005)	0.012** (0.006)
Log (Turnover)	-0.005 (0.005)	-0.008 (0.007)
Free-float Inst. Own	0.001 (0.047)	-0.010 (0.052)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	686	686
R-squared	0.112	0.144

The table presents results from event study regressions in which the dependent variable is cumulative abnormal returns (CAR) and the key explanatory variable is uncertainty sentiment in Arabic annual reports. The regressions are reported for the extended event windows, CAR [−1,+15] and CAR [−1,+20]. The table reports results for Arabic-language sentiment extracted using the ArFinSD dictionary. Standard errors (reported in parentheses) are clustered at the firm level. Significance levels are denoted as *** (1%), ** (5%), and * (10%). Control variables include the log of market capitalization, the log of book-to-market ratio, the log of share turnover, and free-float shares of institutional ownership. All regressions include year and industry fixed effects. Sample: 686 annual report filings from Saudi-listed firms, 2018-2023. Abnormal returns are calculated using the market-adjusted model.

Table D.3 (a-3) Cumulative Abnormal Return

Explanatory variables	CAR [−1,+15]	CAR [−1,+20]
Ar.Neg.	-0.934** (0.387)	-0.864* (0.449)
Log (Size)	-0.002 (0.005)	-0.004 (0.006)
Log (B/M)	0.016*** (0.005)	0.012* (0.006)
Log (Turnover)	-0.005 (0.005)	-0.008 (0.007)
Free-float Inst. Own	-0.004 (0.047)	-0.013 (0.052)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	686	686
R-squared	0.118	0.147

The table presents results from event study regressions in which the dependent variable is cumulative abnormal returns (CAR) and the key explanatory variable is negative sentiment in Arabic annual reports. The regressions are reported for the extended event windows, CAR [−1,+15] and CAR [−1,+20]. The table reports results for Arabic-language sentiment extracted using the ArFinSD dictionary. Standard errors (reported in parentheses) are clustered at the firm level. Significance levels are denoted as *** (1%), ** (5%), and * (10%). Control variables include the log of market capitalization, the log of book-to-market ratio, the log of share turnover, and free-float shares of institutional ownership. All regressions include year and industry fixed effects. Sample: 686 annual report filings from Saudi-listed firms, 2018-2023. Abnormal returns are calculated using the market-adjusted model.

Table D.3 (b-1) Cumulative Abnormal Return

Explanatory variables	CAR [−1,+15]	CAR [−1,+20]
En.Pos.	0.016 (0.347)	0.137 (0.386)
Log (Size)	-0.002 (0.005)	-0.005 (0.006)
Log (B/M)	0.016*** (0.005)	0.012* (0.006)
Log (Turnover)	-0.005 (0.005)	-0.008 (0.007)
Free-float Inst. Own	0.001 (0.048)	-0.010 (0.053)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	686	686
R-squared	0.112	0.144

The table presents results from event study regressions in which the dependent variable is cumulative abnormal returns (CAR) and the key explanatory variable is positive sentiment in English annual reports. The regressions are reported for the extended event windows, CAR [−1,+15] and CAR [−1,+20]. The table reports results for English-language sentiment extracted using the Loughran and McDonald (2011) dictionary. Standard errors (reported in parentheses) are clustered at the firm level. Significance levels are denoted as *** (1%), ** (5%), and * (10%). Control variables include the log of market capitalization, the log of book-to-market ratio, the log of share turnover, and free-float shares of institutional ownership. All regressions include year and industry fixed effects. Sample: 686 annual report filings from Saudi-listed firms, 2018-2023. Abnormal returns are calculated using the market-adjusted model.

Table D.3 (b-2) Cumulative Abnormal Return

Explanatory variables	CAR [−1,+15]	CAR [−1,+20]
En.Unc.	-0.033 (0.367)	-0.249 (0.418)
Log (Size)	-0.002 (0.005)	-0.005 (0.006)
Log (B/M)	0.016*** (0.005)	0.012** (0.006)
Log (Turnover)	-0.005 (0.005)	-0.008 (0.007)
Free-float Inst. Own	0.001 (0.047)	-0.010 (0.053)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	686	686
R-squared	0.112	0.144

The table presents results from event study regressions in which the dependent variable is cumulative abnormal returns (CAR) and the key explanatory variable is uncertainty sentiment in English annual reports. The regressions are reported for the extended event windows, CAR [−1,+15] and CAR [−1,+20]. The table reports results for English-language sentiment extracted using the Loughran and McDonald (2011) dictionary. Standard errors (reported in parentheses) are clustered at the firm level. Significance levels are denoted as *** (1%), ** (5%), and * (10%). Control variables include the log of market capitalization, the log of book-to-market ratio, the log of share turnover, and free-float shares of institutional ownership. All regressions include year and industry fixed effects. Sample: 686 annual report filings from Saudi-listed firms, 2018-2023. Abnormal returns are calculated using the market-adjusted model.

Table D.3 (b-3) Cumulative Abnormal Return

Explanatory variables	CAR [−1,+15]	CAR [−1,+20]
En.Neg.	-1.005** (0.402)	-1.026** (0.466)
Log (Size)	-0.002 (0.005)	-0.004 (0.006)
Log (B/M)	0.015*** (0.005)	0.011* (0.006)
Log (Turnover)	-0.005 (0.005)	-0.008 (0.007)
Free-float Inst. Own	-0.006 (0.047)	-0.016 (0.052)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	686	686
R-squared	0.119	0.148

The table presents results from event study regressions in which the dependent variable is cumulative abnormal returns (CAR) and the key explanatory variable is negative sentiment in English annual reports. The regressions are reported for the extended event windows, CAR [−1,+15] and CAR [−1,+20]. The table reports results for English-language sentiment extracted using the Loughran and McDonald (2011) dictionary. Standard errors (reported in parentheses) are clustered at the firm level. Significance levels are denoted as *** (1%), ** (5%), and * (10%). Control variables include the log of market capitalization, the log of book-to-market ratio, the log of share turnover, and free-float shares of institutional ownership. All regressions include year and industry fixed effects. Sample: 686 annual report filings from Saudi-listed firms, 2018-2023. Abnormal returns are calculated using the market-adjusted model.