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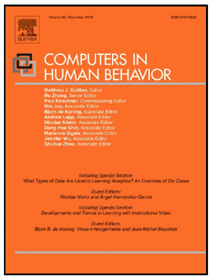

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ABSTRACT

In this study, we explore the interaction network properties of Microblogging Word of Mouth (MWOM), and how it is utilized by two different types of service providers, namely entrepreneurial and conventional. We use social network analysis, involving network metrics, sentiment, content and semantic analysis of real time data collected via Twitter, to compare two providers in terms of how they leverage MWOM in their social interactions. Results demonstrate that MWOM is utilized in an inherently different manner by an entrepreneurial provider, compared to a conventional one. Based on the findings, the study identifies distinctions between the entrepreneurial and conventional service providers in how they utilize MWOM on social media. Specifically, the entrepreneurial provider capitalizes on the interactive nature and dialogic capabilities of Twitter; whereas the conventional provider mostly relies on focal information sharing, thus neglecting the network members' content creation and relationship building capability of social media networks. The study has significant implications as it provides key insights and lessons in terms of how companies should respond to emerging digital opportunities in their online social interactions.

Keywords: Microblogging word of mouth (MWOM); Entrepreneur; Social media; Twitter Structuration Theory

1. INTRODUCTION

The use of social media is an emerging research area where businesses can flourish with their creativity, and can define and communicate their unique identity and image in the minds of their stakeholders. Given the importance of using social networking sites such as Twitter for successful marketing practice, the manner by which different firms (e.g. conventional versus entrepreneurial businesses) capitalize on them and their properties, shapes business and marketing outcomes, and represents an increasing and important research avenue with practical relevance (Anderson et al. 2015).

As a social media tool utilized by organizations, microblogging word-of-mouth (MWOM) is a specific form of electronic-word-of-mouth (e-WOM) within the context of Twitter, given its rise as the most influential and popular microblogging social media platform (Jin & Phua 2014; Hennig-Thurau, Wiertz & Feldhaus 2015). Twitter yields effective MWOM as individuals express their opinions and sentiments that impact other members of the social network. While similar to e-WOM- which reflects positive or negative statements made online about products or services accessed by a large number of individuals instantly (Hennig-Thurau et al., 2004; Christodoulides, Michaelidou & Argyriou, 2012; Kim, Sung & Kang 2014; Kim et al. 2016)- MWOM is brief, encompassing of short and frequent, informal social media communications directed at other people within the context of Twitter about an object or topic, [e.g. products or services, brands, their characteristics, and their providers] (Hennig-Thurau, Wiertz & Feldhaus 2015). MWOM is generated by social media users, for example individuals, firms or organizations (actors) to express their thoughts and views about a topic and it is used by managers as a form of social capital as it allows the connection and interaction of different individuals (Jin 2013; Jin & Phua 2014; Phua & Jin 2011; Williams 2006). Within Twitter, MWOM is generated by individual actors and it is seen as more credible and trustworthy, relative to communication sent from businesses (de

Mator, Alberto & Rossi 2008). MWOM is also likely to influence individuals' purchases of products and services (Hennig-Thurau et al. 2004; Hennig-Thurau, Wiertz & Feldhaus 2015). Despite the increasingly vast usage of MWOM, research on the concept is still in its infancy (Hennig-Thurau et al. 2015). In particular, the properties of MWOM and how businesses leverage MWOM for marketing remains largely unattended. However, understanding the properties of MWOM and how it is leveraged by different types of businesses (e.g. conventional and entrepreneurial) offers new and significant theoretical and practical insights. For example, entrepreneurial businesses have been traditionally inclined to rely on Word-of-Mouth (WOM) communication as a tool for customer acquisition (Stokes & Lomax 2002). Additionally, such firms tend to be digitally-minded, and thus are expected to be more *proactive* in using MWOM [e.g. for community and content co-creation (see also Kleijnen et al. 2009)], relative to conventionally established businesses.

The present study investigates MWOM with the aim to identify its interaction characteristics and utilization among network members within the context of Twitter, as MWOM is seen as synonymous to this specific platform (Jin & Phua 2014). In particular, we focus on identifying differences in leveraging of MWOM between conventional and entrepreneurial businesses (see also Ostrom et al. 2015). In addressing the above objectives, and in line with previous research (e.g. Kalanda & Brown 2017), we follow an indeterminist approach (Kato 2014) to draw on some concepts and ideas of structuration theory (Giddens 1984), as a 'viable platform' which enables the identification, assessment and explanation of social interactions (Stewart & Pavlou 2002, p. 377). More specifically, structuration theory guides our study given that MWOM is a novel concept, currently is its infancy, and reflecting a type of interaction within a social network system. Structuration theory enables us to draw on some of its ideas, and particularly, the notions of interaction and structure, in order to understand MWOM's properties, and how its leveraging differs between service providers. As such, we explore the notion of "interaction" within social networks (MWOM/Twitter) which is underpinned by structuration theory. At the same time, we draw on the notion of structure, which reflects resources and exploitation of opportunities (Sarason et al. 2006; Stewart & Pavlou 2002; Jones & Karsten 2008) to compare two different companies. In particular, we focus on the principle which asserts that the interaction among members of a network (e.g. customers of a business) relates to the structure, in terms of resources and opportunities, of a business (e.g. domination) (Orlikowski 1992; Stewart & Pavlou 2002; Sarason et al. 2006). Two research questions guide our study, RQ1: What are the power interaction characteristics of MWOM? and RQ2: What are the differences in the utilization/leveraging of MWOM between different types of businesses (conventional vs. entrepreneurial)? though both at the domination structure in terms of resources and opportunities.

To the authors' best knowledge this study represents the first attempt in exploring MWOM characteristics and the differences in its utilization/leveraging by different types of firms, linking to notions from structuration theory. The study contributes to the understanding of how different types of companies capitalize on emerging content (e.g. MWOM) on digital platforms. In this way, we produce novel insights with theoretical contributions as we examine a novel social media concept, namely MWOM, which reflects interaction within a social network of actors utilizing structuration theory notions (e.g. the notion of interaction within a social system and actors, being a key element of structuration theory, Giddens 1984). Additionally, we extend prior research which links structuration theory to the study of digital phenomena (e.g. Jones & Karsten 2008), and contribute to structuration theory by demonstrating how interaction exchanges are manifested in a digital social network context.

Thus, we provide novel evidence that structuration theory is theoretically relevant in this domain of research, and that it can offer distinct insights with useful managerial implications. Concomitant to this, the study is practically relevant as it uses live Twitter data, to identify, assess and classify five novel MWOM interaction differences, that characterize the marketing and communication practices of conventional and entrepreneurial businesses. The identification of these five interaction differences offers practical implications, as it provides valuable insights or lessons into how businesses should leverage digital social networks (e.g. MWOM) for effective marketing and communication strategies, as well for creating new ventures and business models. The following section reviews related literature on structuration theory, which provides insights into understanding interactions in social media networks (Stewart & Pavlou 2002), and MWOM. Subsequent to this, the methodology, analysis and findings are presented. Discussion of the findings, limitations and future research conclude the paper.

2. THEORETICAL BACKGROUND

2.1. Structuration theory

Stewart and Pavlou (2002) argue that structuration theory addresses customer and business interactions, as well as the structural contexts which guide these interactions. The application of the theory and its relevance to empirical research has been often labelled as problematic (Jones & Karsten 2008), mostly applied within the remit of interpretivism and using qualitative methodologies (e.g. Kalanda & Brown 2017; Nicholson et al. 2013). Additionally, this theory is highly abstract, rather than being applicable or instantiated within a specific context (Jones & Karsten 2008; Stones 2005). Never-the-less it encompasses concepts which are useful to explore elements of social interactive processes between customers and businesses, in an attempt to identify and evaluate how companies leverage or adopt new and emerging digital opportunities (e.g. social media). Prior research has drawn on concepts of structuration theory individually or in combination, adopting mostly a flexible and indeterministic approach (Kato 2014), in multiple domains including management, management accounting, consumer culture, information systems and e-commerce (e.g. Macintosh & Scapens 1990; DeSanctis & Poole 1994; Barley & Tolbert 1997; Algesheimer & Gurau 2008; Chiasson & Saunders 2005; Jones & Karsten 2008; Nicholson et al. 2013; Chang 2014; Lindridge & Eagar 2015; Kalanda & Brown 2017). Additionally, several authors have highlighted the benefits of drawing on structuration theory concepts in the domain of information technology (Gregor & Johnston 2000; Chatterjee et al. 2002; De Vaujany 2008; Greenhalgh & Stones 2010).

The theory focuses on the social interaction that happens among actors or members of a social network. Giddens (1984) asserts that business and marketing activities are recursive in that the activities are created and recreated by social actors, who reproduce or redefine the conditions for the activities to happen. The above notion signifies the reflexive form of knowledgeability of the actors involved.

Structuration theory highlights two essential elements, namely *interaction*, and *structure* on which we specifically draw on in this study, as they reflect useful elements for understanding MWOM and how it is leveraged by different firms. Particularly, we focus primarily on the premise of interaction- which indicates the activity within the social system (e.g. social network) focusing on space and time (Giddens 1984)-and how it is manifested by actors within the social network to produce or re-produce properties of an interactive system toward achieving desired outcomes (Stewart & Pavlou 2002*)*. Interaction appreciates the reflexivity of actors (human agents) within the social system the actors are in. Additionally, actors are both enabled and constrained by structures (e.g. resources and opportunities), and yet the structures may be the outcomes of interaction among actors (Sarason et al. 2006). According to Orlikowski (1992), there are three types of structures namely, *signification, legitimation and domination* (Stewart & Pavlou 2002). Structures of signification reflect rules that make up meaning (Stewart & Pavlou 2002), structures of legitimation are the norms and rules that allow actors to justify their actions, while structures of domination reflect 'asymmetries in resources' (e.g. knowledge, financial assets and technology), that actors draw on to exercise power to achieve their goals (Stewart & Pavlou 2002). Sarason et al (2006) suggests signification is more likely to occur during discovery of opportunities; legitimation is more likely during evaluation of opportunities, and finally domination is more likely during exploitation of opportunities. Stewart and Pavlou (2002) further suggest that interaction indicates a form of communication during signification, sanctions during legitimation, and power during domination (also Sydow & Windeler 1998). In line with our research questions, our study focuses on power interaction to examine characteristics of MWOM and how it's leveraging varies across different types of companies in domination structure (e.g. in terms of resources and opportunities identified, Sarason et al. 2006).

2.2 Power Interaction Characteristics of MWOM

The proliferation of interactive communication technologies, has enabled more informational and reflexive actions to be performed, offering value meaning and clarity in a far more transparent way. This transparency, wealth of information, value meaning and clarity are then viewed as the norms and rules that guide members of a social network to reflect, interact and communicate among them. The rise of real-time interactive social media has created new conversation channels that have significantly affected how people communicate with one another (e.g. Godes et al. 2005; Hennig-Thurau et al. 2010). The popularity of MWOM has gained traction as it enables members of the network (actors) to share service impressions with the sender's social network or service community in real-time. In this paper, MWOM refers to *"any brief statements made by a consumer about a commercial entity or offering that is broadcasted in real time to some or all members of the sender's social network through a specific web-based service"* (Hennig-Thurau et al. 2015).

MWOM can be viewed as *interaction* among all actors. All interactions, namely transactions, conversations and relationships, contain a level of exchange, the objectives of which encompass both economic value and social capital (Cropanzano & Mitchell 2005). Therefore, when an episode of interaction occurs, there must be some shared value between individuals in a variety of forms. MWOM can be effective to influence actors' behavior as it is perceived as a very dynamic form of interpersonal interaction that goes beyond commercial information exchanges (Kozinets et al. 2010). However, little is known about the interaction properties of MWOM.

The most important aspect of MWOM is its potential for both consumers and businesses to create personalized, two-way communication. Simmons (2006) suggests that real-time, one-to-one interactive communication helps to create more customized brand experiences in line with the consumers' growing need for self-expression and individualism. The increasing use of interactive communication technologies, combined with the growing effort of businesses to fulfil individual needs, is arguably shifting the market power more and more towards the consumer (Pires et al. 2006). Thus, even though interactive communication technology is significantly more effective when it is personalized (Ansari & Mela 2003), Pires et al. (2006) argue that it is necessary to explore the marketing processes that allow consumers' growing empowerment.

From a 'value co-creation' angle, MWOM may provide a significant platform for consumer actor engagement (Chandler & Lusch 2015). Such engagement reflects a form of social and interactive behavior, therefore social networking sites, such as Twitter, serve as ideal platforms where consumer actors participate in collaborative recommendations and development for specific products, services, and brands – through MWOM (Ramaswamy 2009). For example, prior research suggests that Twitter enables MWOM with users sharing brand-affecting thoughts and feelings with almost anyone who is online (Jansen et al. 2009; Jin & Phua 2014). There is empirical support for treating feelings as information (Schwarz & Clore 1996) and as MWOM offers value, increased interpersonal influence on the brand reduces marketing costs and empowers the community to generate new ideas (*see also* Van Doorn et al. 2010).

2.3 Interaction differences in MWOM between Entrepreneurial and Conventional Service Providers

When considering the "dynamic process whereby structures come into being" (Giddens 1976:121), Giddens suggests framing layers of consciousness and action, which may be implicated in the production and reproduction of social systems (Bryant et al. 1991). Consequently, structuration theory provides a sound theoretical compass through framing interactional layers (representing dynamic process of conscious and active interaction exchanges in an existing structure) for distinguishing MWOM characteristics and its utilization as a social networking tool between firms (e.g. entrepreneurial and conventional firms). This is in line with similar research looking at online networks, drawing on specific aspects of structuration theory (e.g. Kalanda & Brown 2017; Kaewkitipong et al 2016; Christopherson 2007). MWOM's characteristics and differences in its utilization as a social networking tool vary between different types of firms (e.g. entrepreneurial and conventional firms) with similar resources and technological opportunities, and present a novel and exploratory research enquiry. Characteristics of MWOM include the level of interactions (e.g. reciprocal action and influence) between actors in a social media network, how firms are managing their interactivity, how the value of offers is signaled and marketed; ultimately indicating differences between conventional and entrepreneurial forms with similar technological opportunities in terms of social media exploitation (e.g. domination structure).

The salient characteristics of entrepreneurial firms have been well documented in entrepreneurship theory in terms of the methods and practices that reflect how a firm operates rather than what it does (Lumpkin & Dess 1996). Miller's (1983, p.71) original conceptualization has been used as the basis for this distinction; "*An entrepreneurial firm is one that engages in product market innovation, undertakes somewhat risky ventures and is first to come up with 'proactive' innovations, beating competitors to the punch"*. Entrepreneurial firms or ventures (e.g. Airbnb)– unlike conventional ones – are innovative (e.g. Drucker 1985), seeking novel ways to bring entrepreneurial concepts to fruition (Bhuian et al. 2005), they manifest a willingness to introduce new products/services or technologies, enter new markets and finally engage in product-service innovation (Avlonitis & Salavou 2007). These tendencies are vividly expressed in high-technology ventures that face rapidly changing environments, accelerated product development and market volatility (Wu 2007). As the digital economy develops, entrepreneurial activities within a digital context - such as a new business model of digital services and/or distribution (Esmaeeli 2011; Turban et al. 2008; Dutot & Van Horne 2015) - are perceived as one of the most important drivers for competitiveness and economic growth, highlighting the instrumental role of emerging technologies in business (Hernandez-Perlines 2016). Nambisan (2016, p.1033) discusses this in the context of Airbnb: For example, when Brian Chesky and Joe Gebbia launched their venture in 2007—which later pivoted to Airbnb—their initial focus was on meetings and events for which hotel space was sold out. However, soon they discovered that such demand for affordable accommodation existed year-around internationally and scaled up their services rapidly. Thus, digital infrastructures infuse a level of fluidity or variability into entrepreneurial processes, allowing them to unfold in a non-linear fashion across time and space.

A substantial difference between entrepreneurial and conventional businesses with the same social media opportunities (e.g. utilization of Twitter) is how they capitalize on MWOM power interaction characteristics (e.g. how interactivity is managed) to market their offerings (Hull et al. 2007). While marketing signifies value-added offerings to consumers, it comes with a variation of interaction among actors. On a social media network (such as Twitter), value is communicated dynamically not only through marketers, but also through other special actors (e.g. a CEO) that shape, formulate and influence value in their own way. This is of sheer importance for entrepreneurial ventures which rely on the influence of these actors to build trust, consumer rapport and communicate with customers in real-time. For example, Tesla and Space X CEO Elon Musk is well known for using Twitter to announce new-to-the-world products and company milestones, thus enhancing the level of interaction with the company. Richard Branson epitomizes the social CEO persona by directly tackling customer complaints; while Google CEO Sundar Pichai's response to a 7-year old's job application became a viral sensation overnight.

In addition, entrepreneurial ventures are characterized by foresight for market change and social media represent an experimentation platform for testing new products and services via social interactions with target customers. This is important, as MWOM facilitates social interaction (Fischer & Reuber 2011), enabling entrepreneurial firms to leverage its relationship-building capability in a more dynamic way. In turn this expands social networks and online communication in the pursuit of new ideas. However, this particular process is not commonplace in conventional businesses where scholars demonstrate that interactivity is mostly leveraged in a less dynamic manner, primarily for customer relationship management (Trainor, Andzulis, Rapp & Agnihotri 2014) or brand management (Asmussen, Harridge-March, Occhiocupo & Farquhar 2013). The tendency of a firm to 'champion' the technological forefront of their market is therefore, an ideal representation of the entrepreneurial archetype, vis-a-vis the conventional one, reflecting that while opportunities are present for both firms (e.g. domination structure, Sarason et al. 2006) the level of interaction and engagement, and how it is managed with different actors varies between service providers.

Furthermore, Shane and Venkataraman (2000) positioned the entrepreneurial firm type within the context of the opportunities they discover, albeit to make progress in opportunity exploration, entrepreneurs need to act (McMullen & Shepherd 2006). Digital and online communication technologies, such as social networking sites (e.g. Twitter), play an important and recurring role in leveraging or exploiting business opportunities as they facilitate the establishment of a dialogue between the firm and its customers (Hair et al. 2012). However, while having the same resources and technological opportunities in terms of Twitter and MWOM utilization, conventional and entrepreneurial firms may differ in how they market or signal their offerings (Kirmani & Rao 2000). This is because, to reduce the observed information asymmetry between seller and buyer, entrepreneurial businesses would be expected to focus on signaling mechanisms that reduce uncertainty and incentivize transactions (Giones & Miralles 2015a). More specifically, in offerings that involve technology as part of the digital business model, the process of delivering or signaling offers is inherently different, compared to those ventures that rely on more conventional means; such that the entrepreneurial business is expected to be *more flexible, participative and* *adaptive*' within their network (Duchesneau & Gartner 1990). Entrepreneurial businesses thus embrace, keep and grow digitally-born opportunities such as MWOM, while conventional businesses superficially embed digital technology into their services, without fully leveraging opportunities to signal and market their offerings via interactions.

Differences in signaling offerings between service providers may become clear when looking at affective and cognitive properties of MWOM, with research highlighting the importance of user-generated content sentiment (Ludwig et al. 2013). Indeed, sentiment provides a useful conduit for understanding tone and consumer participation (Ordenes et al. 2017); for example, entrepreneurial businesses are more likely to initiate consumer participation as they signal their offerings, compared to conventional businesses. On the basis of the above discussion we offer two propositions:

P1: Conventional and entrepreneurial businesses [both at domination structure in terms of resources and MWOM technological opportunities] use MWOM to interact with actors; the level/depth of interaction, and how interaction is managed will be different between service providers, such that entrepreneurial service providers being more dynamic and engaging, within their network relative to conventional providers.

P2: Conventional and entrepreneurial businesses [both at domination structure in terms of resources and MWOM technological opportunities] capitalize on MWOM to market their offerings; however, they signal them in a different manner with entrepreneurial firms being more flexible and participative in signaling offerings, relative to conventional businesses.

The following sections present the methodology, followed by the analysis and results. The paper ends with a discussion of the findings highlighting theoretical and practical contributions.

3. METHODOLOGY

3.1 Industry Context

In line with previous research, and given the flexibility that structuration theory offers to examine individual elements or concepts, the paper investigates the power interaction characteristics of MWOM focusing specifically on companies at domination structure (in terms of resources and technological opportunities involving capitalization of Twitter and MWOM) within a service context. We selected accommodation provision as the context, because this specific service type provides greater opportunities for interaction between stakeholders and actors on social networking sites. In particular, we focus on two accommodation providers namely, Airbnb and Holiday Inn. These two accommodation providers are at domination structure in terms of resources (i.e. well established and large business-scale firms), and are valued higher than US$ 1 Billion, with the same technological opportunities (in terms of usage/ capitalization of Twitter and MWOM). For example, in 2016 Airbnb had received more than $1.6 billion accumulated funding (Figure 1). Similarly, Holiday Inn is one of the largest hotel groups in the accommodation industry. However, in terms of types of firms, Airbnb is a privately owned, unique representation of the entrepreneurial firm and one of the fastest growing accommodation providers. Albeit, Holiday Inn is an established brand and a conventional type of provider. The both operated at a global scale; and while at domination structure in terms of resources and social media opportunities, the two providers reflect sufficient variation in terms of their business model (type of company), that enables a profound comparison on how they leverage MWOM. For example, Airbnb embraces the principle of sharing economy through online media, where multiple member actors share their accommodation resources and are active in creating and recreating value. In doing so, Airbnb provides a platform where member actors can advertise their available rooms. On the other hand, Holiday Inn operates as a conventional accommodation provider and marketer.

Figure 1 here.

3.2 Data Collection and Analysis Method

MWOM was captured using real time data from Twitter due to its pervasive use among related stakeholders. Twitter is the most popular MWOM-enabled platform and its imposed 240-character limit provides certain options in terms of content generation and sharing. Users have the opportunity to add pictures, videos and web links (URLs) to their text messages, and as a result there is a potential for creating buzz. Firms can generate content to engage with their audiences, whereas audiences can actively participate with the creation of content directly related to the firm.

Primary data were collected using the built-in Twitter API search tool in NodeXL, which provides live data crawling and social network analysis capabilities. The extraction procedure included identifying and selecting the entrepreneurial ("AirBnB") and conventional ("Holiday Inn") service provider public usernames to allow for extraction of their Twitter network edges for further analysis. Once tweets were extracted in raw form, data were cleaned so that groups of networks only contained tweets exclusively about each service provider. The process eliminated duplicate edges, noisy and redundant data (Smith et al. 2009). Data contained information on the types of relationships that connect Twitter users. Hashtags were included, being the most commonly used form when providing information on a particular topic. Sample also contained replied-to ties, an integral Twitter feature that allows users to reply to other user's messages, demonstrating an organic stance to MWOM. Finally, the sample also contained mentions, a feature that represents the influence of a Twitter user which was used in later stages in our analysis. Table 4 provides the dataset tweet profile in detail. Following the process, a total of 5,293 usable tweets were collected during June 2016.[1]

To explore how both firms (Airbnb and Holiday Inn) leverage MWOM for interaction with their customer actors (P1) and for signaling and marketing their offers (P2), network metrics analysis, content analysis (e.g. sentiment analyses) were conducted; as they are useful to explore the characteristics of the interaction among actors within the MWOM Twitter network (Groeger & Buttle 2016; Lerman & Gosh 2010) .The first analysis, the network metrics, consists of three subgroups, namely aggregate (or overall) network metrics, vertex/actor specific network metrics and network graphs of specific actors. These networks metrics are metrics that reveal the network mathematical/numerical properties and insights of the interactions among actors take place, i.e. mathematical map and characteristics of the interactions/inter-connections/inter-relationships among actors that exist in the Twitter microblogging network. In sum, network metrics help to unveil the metric properties of the overall network and specific-actor network.

[1] 2016 has been a crucial year for Airbnb. The company's valuation increased at around $30 billion – remaining among the top 4 most valuable privately-held companies in the world and moving from a 'unicorn' to a 'decacorn' status. In addition, Airbnb turned profitable in the second half of 2016 and launched a new digital marketing campaign called 'Live There'. This is the exact stage where Airbnb reached domination structure (Stone 2017; O'Brien 2016; Newcomer & Barinka 2016).

The second group, namely content analysis, consists of six subgroups, such as tweet profile, top hash-tags, top replied-to, top mentioned, sentiment analysis and semantic analysis. This content analysis specifically reveals the content (how tweets being generated and spread, sentiment and semantic/word clouds/topics) properties and insights of the interactions/inter-connections/inter-relationships among actors that exist in the Twitter microblogging network. Twitter profile (table 4) helps unveil the generation and spreading properties of the contents generated by actors as well as unveil the role/positioning of the focal actor(s) and related actors and topics. Top hash-tags, top replied-to and top mentioned (tables 5, 6 and 7 respectively) enable us to find the most frequent topic tweeted by hash-tags, and which actors have been most frequently replied-to and mentioned in the data set. Sentiment analysis (table 8) unveils the affective, cognitive and drive contents of Twitter in the interactions among actors in the networks, thus showing the depth of interaction (P1), allowing us to also identify how participatory is the interaction to signal offerings (P2). On the other hand, semantic analysis (fig. 3 & 4) is useful to unveil how dynamic is the interaction by identifying most frequent words used in the interactions among actors, and, specifically help to explore the role of the focal actor(s) of each of the firms and the topics surrounding them. Both semantic and sentiment analyses have been useful for understanding content, tone and involvement of interactions among actors (e.g. Ludwig et al. 2013; Ordenes et al. 2017; Zavattaro et al. 2015). Overall, both network metrics and network content analysis in fact contribute to unveiling the insights into both propositions (see table 1), where all the analyses provide insights to address our theoretical propositions. As our study is exploratory in nature, the integrated approach in using the analytical findings helps to have some sort of comprehensiveness or cross-validation to our discussion and interpretation.

In terms of software selection, NodeXL is one of the most popular open source template integrating the most commonly used network metrics and graph layout algorithms for social network analysis (Hansen, Shneiderman, & Smith 2011). For the purposes of semantic analysis, the study used Wordij 3.0 which is a family of computational algorithms designed to automate content analysis by analyzing co-occurrence of word pairs. Finally, for sentiment analysis the latest version of Linguistic Inquiry and Word Count (LIWC) has been utilized (Pennebaker, Chung & Ireland 2007), which is a text analysis software platform assessing the emotional, cognitive and structural components of texts using a psychometrically validated internal dictionary. Its reliability (e.g. Pennebaker and King, 1999) and validity (Pennebaker, Mehl & Niederhoffer 2003) are well documented (Pennebaker 2017). In sum, network analysis (metrics and content) is effective to comprehend the interactions among actors within a social network (Wasserman & Faust 1994). It allows for the exploration of structural relationships of content generated by social media users. The core advantage of this approach is that natural MWOM text extracted from a social network (in our case, Twitter) is analyzed empirically to provide valuable insights into the structure of a social media community (in our case Airbnb and Holiday Inn). Social networks are characterized by integration and interactivity (Van Dijk 2012). As a consequence, via this analysis we were able to understand the interaction properties and characteristics for each of the selected organizations. Table 1 summarizes these analyses.

Table 1 here

4. ANALYSIS AND FINDINGS

4.1 Networks Metrics

The networks metrics consists of overall networks metrics (Table 2), actor-specific networks metrics (Table 3) and networks graphic profile (Figure 2), that enable us to examine the entrepreneurial characteristics of MWOM. A description of the network metrics is as follows:

- Vertex: a node representing a basic element. Simply, a vertex is a Twitter user.
- Edge: a line tying nodes representing a relationship
- Geodesic distance refers to the shortest path between two nodes in a network.
- Average clustering coefficient is a measure in which if all vertices/nodes are linked to one another. When the clustering coefficient is high for the network, it allows for the visualization and identification of groups within the network.
- Betweenness centrality refers to the number of times a node lies in the shortest path between two other nodes, implying that the node serves as a bridge and can be seen as a measure of the extent to which the removal of the node disrupts links within the network.

Table 2 presents the overall networks metrics that summarizes key properties of the entire network. The remarks in the table describes the meanings of the metric measures.

Table 2 here.

Referring to Table 2, the vertices and total edges reflect the size of Twitter data allowed to be downloaded by Twitter Inc. through NodeXL software. These properties are therefore not to be compared as they are. The geodesic distance, maximum and average, are higher for Airbnb than Holiday Inn, showing that Airbnb covers a wider span of network. The average clustering coefficient suggests that Airbnb network is less clustered compared to Holiday Inn, by nearly a third. In other words, members of Airbnb network are more dispersed than the ones of the Holiday Inn's network. The average betweenness coefficient indicates how central the company is in communicating with the rest of the members within the Twitter MWOM network. Holiday Inn has a much higher level of betweenness (1604) compared to Airbnb (183). This demonstrates that Holiday Inn communicates much more intensively compared to Airbnb when two members of Twitter network tweet each other. Following the overall networks metrics, actor-specific metrics provide a further picture.

Table 3 here.

The results in table 3 suggest that, in comparison to Holiday Inn, Airbnb as an actor within its networks is less in-degree, which means a less focal actor; is less central (with respect to betweenness centrality and closeness centrality); less important/influential (with respect to PageRank), and has more connected clusters (with respect to clustering coefficient). It is worth noting that eigenvector centrality, a variant of PageRank, has somewhat suggested that Airbnb has played a more important and more influential role within its networks. PageRank algorithm is a better measure as it estimates not only the quantity of ties (the actor's degree and the degree of its neighbors), but also the importance/quality of the ties between actors/vertices. Therefore, we used PageRank to represent the importance and influence of the actor/vertex of interest. Following the networks metrics, graphic analysis gave further insights.

Figure 2 here.

Figure 2 visualizes graphically key networks characteristics surrounding Airbnb and Holiday Inn. Holiday Inn (the right graph of Figure 2, with Airbnb as the central node dark blue colored) has been playing much more centralized effort in Twitter communication compared to Airbnb (the left graph of Figure 2, with Airbnb the central node dark blue colored in the central box). Holiday Inn is individually and directly connected to its neighbors that create big clusters centered to it. Airbnb is the opposite, with its network visualized as more networked, less individually connected to its neighbors, and more clustered.

4.2 Content Analysis

To address our second proposition and understand how value is signaled and marketed in Airbnb and Holiday Inn, our second part of analysis reflects the identification of themes within text (Ryan & Bernard 2003). Content analysis involves a tweet profile (Table 4), top hashtag analysis (Table 5), top replied-to analysis (Table 6) and top mentioned analysis (Table 7). Additionally, sentiment analysis was conducted (Table 8), which provided an additional layer of understanding in line with previous research (e.g. Pfeil et al. 2009), allowing us to understand the emotion encoded in text by using a sentiment polarity dictionary and semantic analysis (Fig. 3 & 4). Finally, semantic analysis allowed us to explore of textual content in terms of frequency, occurrence and proximity and to identify the role of the focal actor(s) of each firm, producing normalized counts of word pairs. For easy reading, sentiment and semantic analyses are shown in separate sections, 4.3 and 4.4 respectively.

Regarding the tweet profile, the variables that can be reciprocally generated include the following:

- Hashtags (#): denotes a tweet with a particular topic.
- Retweets (RT): a repost of a message of another user.
- Mentions (@): indicates a user mention.
- URL: the addition of an internet link.

Table 4 provides an overview of the tweet profile for both ventures.

Table 4 here.

Airbnb network members retweeted (RT) 45% of content and also demonstrated a more engaging behavior with the use of hashtags on a consistent basis (56% Airbnb vs. 37% Holiday Inn). As Airbnb's sample contained far more retweeted content and with RT function being accepted as one of the key indicators of MWOM in Twitter social media network (Hoffman & Fodor 2010; Wolny & Mueller 2013), there are clearly identifiable, contextual differences between the two service providers. Airbnb's network relies more strongly on retweets and hashtag use (more multi-way or network communication style), whereas Holiday Inn more depends on mentions to signal the service offers, a rather traditional service marketing approach (more one-to-one-way or more focal communication style). This is an important distinction that highlights the notion of community and content co-creation (Chandler & Lusch 2015; See-To & Ho 2014), and which is consistent with the networks metrics. Airbnb can now be regarded to 'empower' its networks' actors/vertices in generating and sharing user-generated service/offer-related content (tweets) more strongly than Holiday Inn.

Table 5 here

Table 6 here

Table 7 here

The findings of the content analysis indicate exciting conclusions that add to those from networks metrics analysis. More specifically, MWOM actions such as retweets or hashtags should be perceived as quality signals that demonstrate the intention to convey information about the service to stakeholders and potential customers. This is particularly important for

Airbnb as an accommodation service entrepreneur capitalizing MWOM properties to highlight the service qualities and reduce uncertainties and customer skepticism. The capacity of accommodation service entrepreneur to strategically leverage these signals, is highlighted from differences in content creators and the emotional tone of tweets respectively. The fact that for Airbnb one of the top-mentioned terms is Brian Chesky (Airbnb co-founder), demonstrates the importance of individual actors in orchestrating MWOM interaction. On the contrary, Holiday Inn has a very different content creation mechanism, where top mentions predominantly revolve around the brand itself (holidayinn, ihgservice, holidayinn_ptbo). This implies that these service offers are signaled and marketed in inherently different ways. Overall Airbnb tends to play as 'genuine networker' role, which empowers its networks' actors/vertices in generating and sharing user-generated service-related content (tweets). On the contrary, Holiday Inn seems to play as a 'focal', 'individualistic actor' with centralized type of networks who handles or manages the network communication more on its own.

4.3. Sentiment Analysis

Sentiment analysis is revealing of the 'unconscious motives/cognition' repressed semiotic impulses affecting motivation (Bryant et al 1991). It represents an option for better understanding how MWOM interaction properties are manifested by the two different firms, and specifically it allows us to identify how participatory the interaction is and in relation to signaling offerings (P2). By calculating the degree to which a text sample contains words in specific categories, the LIWC2015 software provides empirical values (frequencies) that demonstrate the interpersonal influences on each service. For the purposes of this study, three concepts have been examined namely affective processes (positive and negative emotion), cognitive processes (insight and cause) and drives (affiliation, achievement and risk). Table 8 provides an interesting overview of sentiment findings.

Table 8 here.

There are substantial differences in the affective, cognitive and drive processes of sentiment. Holiday Inn tends to be more affective and less cognitive compared to Airbnb. More specifically, in terms of affective process, Holiday Inn has as higher level of positive emotion (posemo) than Airbnb. Holiday Inn's substantial distance in terms of positive emotions can be interpreted due to the fact that in most of the cases the content has been generated, transcended and managed through the venture itself. Understandably the 'organizational communication language' tends to be more positive than the 'individual/personal communication language'. However, regarding negative emotions (negemo), there was no difference between the two service firms. Additionally, Airbnb, relative to Holiday Inn, scores higher with respect to overall cognitive processes, cognitive insight, cognitive cause, drive to achieve and drive to take risk. However, Airbnb tends to be less affiliative than Holiday Inn. An explanation of this may be related to the newness (innovativeness) of the accommodation service offer, where the offer from Airbnb is relatively 'a new kid on the block' (disruptively innovative) type, whereas the offer from Holiday Inn has been a conventional one, given Holiday Inn's business venturing age.

Connecting the findings of sentiment analysis and the tone of tweets in Tables 5, 6 and 7, there are differences in terms of affective and cognitive processes in Twitter content between Airbnb and Holiday Inn; with the former demonstrating a less affective but more cognitive stance whereas the latter demonstrating the opposite. One possible explanation of such big difference in cognitive processes (and their underlying insight and cause dimensions), may be reflected from the fact that Airbnb tweets make a very strong use of locations due to the Cannes film festival 'theme' which was captured during the data collection; whereas the Holiday Inn tweets reflect a much more brand-oriented identity. Therefore, the cognitive process and drive sentiments within the Airbnb network communication are stronger due to the fact that Airbnb is still improving its service forms and offerings that require cognitive processes. To this end, Airbnb appreciates drives to achieve, to take risks and to be less affiliation-oriented among actors/members of the networks. Contrary, Holiday Inn is relatively less cognitive (due to its established service offerings), less achiever-oriented and risk-taker and more affiliative within its networks.

4.4 Semantic Analysis

As aforementioned, semantic analysis was used to explore at a glance the frequently used key-words (wordcloud or can be called as thematic) and focal actors configuration drawn from the tweets including the level of interaction among these contents (between focal actors and the themes) within the social network. Specifically, the semantic network graphs in Figures 3 and 4 demonstrate the frequent particular words used in Twitter communication network. These words include verbs, Twitter user names, events, or particle words like 'of', 'for' or 'the', the latter of which were excluded from the analysis. Notably, the semantic graph in Figure 3 shows a special actor within the Airbnb network, 'bchesky (and brianchesky)', besides Airbnb itself. Bchesky (and brianchesky) is an internet expert and the owner/founder of Airbnb, and based on the network graph (figure 2) he has a strong Twitter link to Airbnb. This indicates that Airbnb's social network tends to benefit from this internet expert actor due to his followers, and because of being active in sharing information about Airbnb and its service offers in the network. With the presence of a "special actor" the interaction within Airbnb's network is intensified, dynamic and engaging within the social network (P1). Noteworthy, an additional frequently used word within the network of Airbnb is that of ‘canneslions’, and this is explained by the fact that Twitter data was collected during the Cannes’ film festival (also table 5 above).

Figure 3 here.

Semantic analysis for Holiday Inn (Figure 4) demonstrates quite different findings. With words like ‘holidayinn’, ‘holidayinn_ptbo’, ‘hotel’, ‘joyoftravel’, ‘trip’ and ‘ihgservices’, Holiday Inn is found to be consistently marketing themselves through its personal brand and corresponding key service stimuli. Relative to Airbnb, analysis indicates no special actor within the network. In other words, the semantic profile of Holiday Inn confirms the ‘traditional/conventional’ marketing of services, which is centered and managed at large by Holiday Inn itself, although through utilizing Twitter as a communication platform.

Figure 4 here.

5. DISCUSSION

Drawing on structuration ideas (Giddens 1984), this study examined interaction differences in Microblogging Word of Mouth (MWOM) between service providers, focusing specifically on interaction and signaling of offerings. Indeed, the results have highlighted a number of differences, that provide support to the theoretical propositions put forward in the study, and which show that even though accommodation service providers have the same 'strong' structure (e.g. domination) they differ in their social [inter]action. Findings from the different analyses pave the way to comprehend key insights into MWOM’s power interaction characteristics, i.e. power interaction within a domination structure by an entrepreneurial firm (Airbnb) versus a conventional firm (Holiday Inn), and to identify differences in interaction within a social networking platform. More specifically, we identify five key points or domains of differentiation in terms of how MWOM is leveraged by both firms in terms of: 1) the level and dynamism of interaction; and 2) with regard to how participative the different providers are, in signaling offerings on Twitter. Additionally, these domains reflect levels or modes of utilization of MWOM, highlighting how interaction exchanges are manifested in a social networking context, and how an entrepreneurial organization interacts in their social network relative to a conventional provider.

5.1 Level of Interaction

The level of interaction reflects the activity within a social system (Bryant et al. 1991) and enables us to draw on particular properties of networks and yield useful insights and conclusions. MWOM as an 'interaction' reflects the communication and engagement among actors within a social network (e.g. Twitter), indicating how content is produced and re-produced by different actors, in order to leverage opportunities (Stewart & Pavlou 2002). Such opportunities while present for different types of firms (entrepreneurial vs. conventional) though with similar/same resources (e.g. domination structure), they are not taken advantage of. In particular, the results of this study show that, Airbnb, as an actor within its networks, is less focal, less central, (e.g. figure 2) less important and/or influential, and has more connected clusters; relative to Holiday Inn which seems to be a 'focal', individualistic actor with centralized type of MWOM network, and which handles or manages the communication more on its own. Consistent with this notion, the content analysis suggests that Airbnb is more dynamic in that it empowers its network' s actors/vertices in generating and sharing user-generated service-related contents (tweets), that enhance communication and often generate ideas. In other words, Airbnb tends to be more interactive and more empowering, thus leveraging MWOM properties to a greater extent. Additionally, semantic analysis shows the existence of a special actor (owner, founder, expert) within Airbnb's social network, which is of nonexistence in the case of Holiday Inn. In line with Giddens (1984), special actors within social media networks allow the entrepreneurial firm to leverage the actors' followers to share information about services within the network, thus enhancing the interaction by producing and encouraging re-production of communication making it more dynamic and engaging within the social network.

Further, in view of Airbnb's more 'democratic/empowering/decentralized' social network profile, the analysis suggest that Airbnb has a more transparent, risk-taker, and achiever-oriented style of power interaction at its domination stage. This means that Airbnb as an entrepreneurial firm is more dynamic, identifying opportunities within its network and capitalizing MWOM to a fuller extent. On the other hand, Holiday Inn's sentiment profile, which reflects a more 'focal/centralized' social network, suggests a more controlled, risk-averse and more affiliating orientation style of power interaction at its domination stage. These findings provide support to the theoretical proposition (P1), and extend past research (Fischer & Reuber 2011), highlighting that relative to conventional service providers, entrepreneurial firms have a wider social network interaction with their customers, and are more dynamically-driven to leverage MWOM in organizational practices (Asmussen et al. 2013). Conversely, we identify that the social network of the conventional service provider is more controlled and utilized in an 'authoritative' way. These results suggest that conventional service providers should seek to enhance their digital social networks by capitalizing MWOM to a fuller extent, and by being more dynamic and engaging.

5.2 Signaling of Offerings

Past research indicates that service offerings within social interactions are signaled in an inherently different manner (Giones & Miralles 2015b). Indeed, the analysis has provided key and novel insights on the differences between Airbnb and Holiday Inn in terms of how service offerings are signaled or marketed, thus providing support to P2. More specifically, content analysis indicates that Airbnb is a *genuine networker* that utilizes the network to signal offerings by engaging its networks' members into generating and sharing tweets (user-generated service-related contents). This finding complement previous research which highlights the importance of user-generated content (Ludwig et al. 2013), and indicates that entrepreneurial firms are more flexible and participatory in their networks (Duchesneau & Gartner 1990). Notably, Airbnb as a service offer has been signaled through network participation, and therefore its network members bring their own signals of quality into the offer. In this way, Airbnb seems to be more adaptive on the MWOM, embracing this digital technology as an opportunity to market offerings within the social networking site. Conversely, Holiday Inn as a focal and individualistic actor does not leverage such opportunities; instead, Holiday Inn, as a service offer, is signaled primarily with orientation to its brand, indicating some sort of historical preservation being put into the new 'interaction cloth' of MWOM marketing. This is rather contradicting to conventional service marketing theory that stresses the community-building and content sharing qualities of social media and the fact that firms have the ability to strengthen their service marketing efforts by capitalizing on social technologies (see also López-López, Ruiz-de-Maya & Warlop 2014).

These findings broadly suggest that entrepreneurial firms are likely to signal their offers through network participation, while conventional firms tend to signal their offers with an orientation to the brand. The above ideas suggest a link between how the firm or business was originally created and has become established, and the characteristics of the interaction/communication at domination stage (Giddens 1984; Stewart & Pavlou 2002). Additionally, the results show how social interactions in a digital social network occur, highlighting that companies with similar structure do not necessarily interact in the same way within their social network. In this sense, while technology and in this instance, digital platforms (e.g. MWOM/Twitter) are available for both firms, they are implicated with their actions (e.g. interaction) (Giddens & Pierson 1998; Jones & Karsten 2008); and which differ in terms of how the level of interaction and how they signal offerings. Table 9 below, summarizes the key points of differentiation between the two types of service providers.

Table 9. Summary of Points of Differentiation in Interaction and Signaling between Firms in Leveraging MWOM

Entrepreneurial Firm	Conventional Firm
More network empowering	More focal
Transparent, risk-taker and achievement-oriented	Controlled, risk-averse and affiliating
Special actor in network	No special actor present within the network
Genuine social networker	Focal and individualistic
Signal offerings via network participation	Signal offerings via brand orientation

6. CONCLUSIONS, CONTRIBUTION AND LIMITATIONS

The study examines how MWOM is leveraged by two accommodation service providers. Specifically, we focus on an entrepreneurial accommodation provider (Airbnb) relative to a conventional one (Holiday Inn). Findings based on analysis of real-time data drawn from Twitter, provide key and interesting insights, and are in line with prior research suggesting that entrepreneurial companies [relative to conventional ones] such as Airbnb are innovative, respond to changing environments and trends and capitalize on new technologies

(Esmaeeli 2011; Turban et al. 2008; Dutot & Van Horne 2015). Our study confirms that such firms leverage social media more fully, and particularly MWOM, in interacting, marketing and signaling their offerings. More specifically, our results provide support for the theoretical propositions, and show that the entrepreneurial provider (Airbnb) capitalizes their social network in a greater extent, by being more engaging, participative and adaptive to the dynamic nature of user-generated content. On the other hand, the conventional provider (Holiday Inn) tends to rely more on focal information sharing, thus neglecting opportunities for capitalizing on network members' content co-creation, and relationship building which enhance consumer engagement.

Our study contributes to structuration theory by showing that interaction can manifest in social networking sites (e.g. Twitter), and that the theory is empirically relevant in the domain of digital technologies. Concurrently, the study enhances understanding of how different types of companies capitalize MWOM, and more specifically it extends scholarly research on: a) the interaction properties of MWOM and b) how MWOM is leveraged, as we identify and evaluate five domains or points of differentiation between the two types of service providers. In particular, the findings point to significant implications regarding reflexivity as an essential property of MWOM. For example, results suggest that entrepreneurial providers (such as Airbnb) are likely to be more proactive, flexible and accommodative in the interpretation of social systems i.e. marketing the services, but also the ability to reflect upon and modify interpretations. On the contrary, conventional providers (e.g. Holiday Inn) are likely be more reactive, rigid and controlled over the reflexivity processes in interpreting and re-interpreting the marketing of services. We also find that the duality of domination structure and power interaction is characterized by the marketing communication formality in relation to the existence of special actor. Thus, when it comes to comprehend and model the power interaction style at domination stage (e.g. leverage of opportunities), the existence (or non-existence) of a special actor should be taken into consideration. Last but not least, the origin of the firm (i.e. the origin of their service or product offer) tends to shape the way the firm interacts and leverages MWOM (on Twitter) in marketing their service even at the domination stage of their business history. In other words, the findings suggest that MWOM marketing will still bear certain essential characteristics of how the service offer was born and has grown.

Our study is also managerially relevant and this is evident by the use of real time Twitter data to identify the properties of MWOM and how it is leveraged by two different service providers. As such, in terms of the practical utility and lessons to be learned from our study, as domination structures are perceived as transformative relationships that facilitate goal attainment (Sarason et al. 2006), the use of digital means in key aspects of the value/offer creation and marketing process opens new opportunities and challenges for firms. Businesses nowadays are increasingly dependent on marketing their services on social media, hence MWOM is seen as an essential resource which shapes communication of service offerings. By having ample access to digital resources, entrepreneurial firms embrace more sharing collaborative usage of MWOM with their customer base (e.g. by being more genuine networkers, having a special actor, transparent and risk takers, signaling offers via network participation), and this enables them to explore opportunities for business models involving new digital services or the distribution and promotion of existing service offering online. Conventional firms can therefore learn from entrepreneurial firms in terms of leveraging MWOM more fully as its structural properties influence the effectiveness of communication and interaction within the firm's social network (Stewart & Pavlou 2002).

Finally, in terms of our study's limitations, as social media and their prevalence is relatively new, it is understandable that software or programs available to analyze social media data are still at an early stage of development. Additionally, there are other obstacles such as Twitter does not allow unlimited crawl by NodeXL (understandably this limitation also applies to any other crawl engine or tool), as well as data limitations as access to large quantities of Twitter data have considerable financial cost. Furthermore, analysis of large quantities of Twitter data (Big Data), present a challenge for researchers in view of methodological and analytical inadequacies (Liu et al. 2017). In spite of the above limitations, we attempted in the best possible way in crawling the Twitter data using NodeXL within what Twitter platform allows.

Moreover, every attempt has been made to utilize existing software with robust and careful interpretation. In this paper, we focus on Twitter as it allowed better access (e.g. open platform) specifically while there are other social media platforms such as Facebook and LinkedIn. Hence, future research may aim to direct their focus to alternative social media platforms. Further, the study focused specifically on the domination structure (in terms of resources and opportunities exploitation) and corresponding power interaction, however, future research may aim to investigate other structures (signification and legitimation) and interactions (communication and sanctions). Replication attempts could also include additional measures to enable the exploration of other structures and interactions. Last but not least, despite the fact that our research takes a very important first step for illustrating interaction differences between conventional and entrepreneurial accommodation providers, the service-specific nature of our investigation does not allow for generalizations beyond institutional MWOM. Additionally, we focused on two, albeit varied accommodation service providers, and although in the context of our study this choice served our research objectives and facilitated live-data collection, future research may investigate more firms in other service industries. Indeed, this presents an avenue for future research, to explore the industry-wide interaction properties of MWOM and a more expansive selection of businesses may allow this. By demonstrating that interactivity is managed differently in entrepreneurial firms compared to their conventional, non-internet-native counterparts, we invite future attempts to address specific processes associated with the valence of MWOM.

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Figure 1.
Airbnb accumulated funding indicating a domination stage (circled)

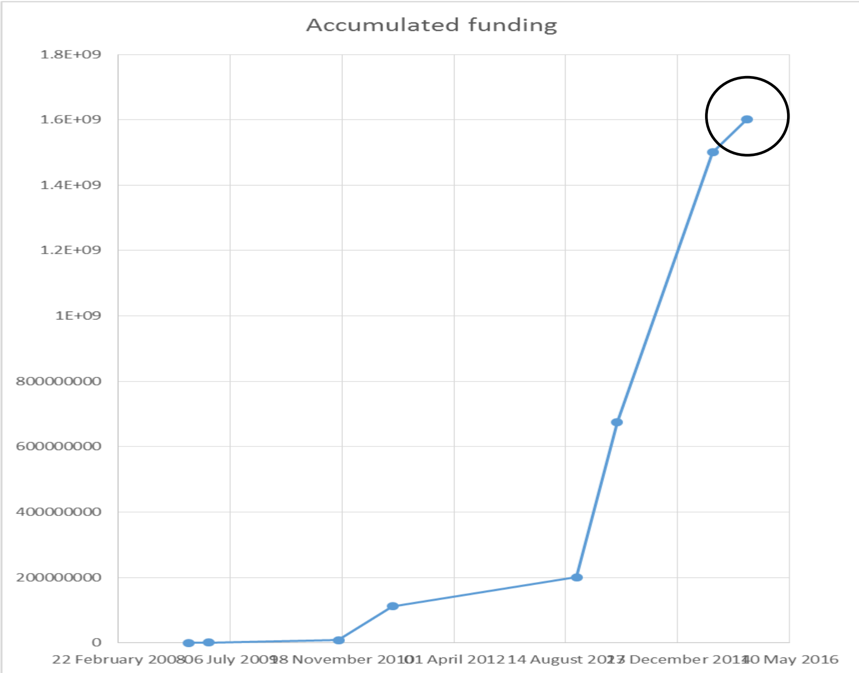


Table 1 Propositions and Analytical Methods

Proposition	Networks Metrics Analysis			Content Analysis					
	Overall Network Metrics	Actor-Specific Network Metrics	Graphic Analysis	Tweet Profile	Top Hash-tags	Top Replied-to	Top men-tioned	Senti-ment Ana-lysis	Seman-tic Ana-lysis
P1	√	√	√	√	√	√	√	√	√
P2	√	√	√	√	√	√	√	√	√
Results shown	Table 2	Table 3	Fig. 2	Table 4	Table 5	Table 6	Table 7	Table 8	Fig 3 & 4

Table 2.
Aggregate Networks Metrics

Measures	Airbnb	Holiday Inn (HI)	Description	Remark
Graph Type	Directed	Directed	Basic information whether graphically the directions of Twitter interactions shown or not. Directed denotes graph type where the directions of Twitter interaction shown.	Directed means a vertex/node/actor may follow without having to be followed.
Vertices	734	1850	Basic information about the total number of actors in the network	Vertex = nodes/ actors/ people
Total Edges	1148	4141	Basic information about the total number of connections/ties/links in the network	Total number of connections /ties /links
Connected Components	273	192	The number of clusters (connected components) exist in the network	Despite the lower number of vertices and edges, Airbnb network has more clusters (connected components) that HI network A connected component = a cluster
Single-Vertex Connected Components	194	139	The number of clusters (connected components) exist in the network	Number of clusters with single vertex
Maximum Vertices in a Connected Component	250	1455	The maximum number of actors (vertices) in a cluster (connected component)	This measure indicates that Airbnb network is more 'decentralized' than HI network
Maximum Geodesic Distance (Diameter)	8	7	The farthest distance (maximum number of hops) a network has	This shows that Airbnb network covers wider network span (8 hops) than HI network (7 hops)
Average Geodesic Distance	3.01	2.39	The average distance (average number of hops) a network has	On average Airbnb network has greater geodesic distance (just over 3 hops) than HI network (2.39 hops), showing that Airbnb network covers

				more friends' friends than HI
Graph Density	0.00132	0.00072	Ratio between the total number of interactions/interconnectedness/rela divided by the total number of possi interactions/interconnectedness/rela	Airbnb social network is much denser than HI network, indicating that the Airbnb network members/actors/agents are more active/communicative than HI network members/actors/agents
Average clustering coefficient	0.064	0.179	Ratio that shows how connected a network in terms of cluster. It shows the average density or concentration of a network in terms of cluster.	HI network as a cluster is more connected than Airbnb network, which means that HI network is more concentrated and Airbnb network is more dispersed.
Average betweenness centrality	183	1604	The average score of an actor bridging (lying on the shortest path between) other actors in a network.	HI network has the highest score, much higher than Airbnb, indicating that within HI network actors/nodes are more bridging for connections between other actors/nodes.

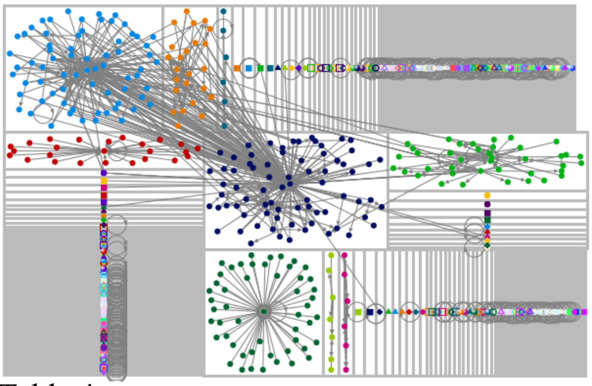
Table 3.
Vertex/actor-specific Networks Metrics

Vertex/Node/Actor	Special vertex/actor				Description	Remark
	Airbnb network			HI network		
	Airbnb	bchesky	Brianchesky	holidayinn		
Betweenness Centrality	47,318	13,059	67	2,092,039	The score of a specific actor in bridging (lying on the shortest path between) other actors in a network.	holidayinn has the highest score here, much higher than the rest, which means most often it is included in the shortest path between two other vertices/nodes/actors
Closeness Centrality	0.0024	0.0017	0.0012	0.0006	The average distance of a specific actor with every other actor in a network. The lower score indicates a more central position of a specific actor in a network.	holidayinn has the lowest score here, which means it is directly the most connected (closest) to most other vertices/nodes/actors in the network
Eigenvector Centrality	0.0551	0.0380	0.0038	0.0278	The influence score of a specific actor for strategically connected people.	holidayinn has the second lowest score here, although the score is not very different from Airbnb or bchesky, which means the second lowest in terms of its own degree plus the degree of vertices directly connected to it. In other words, this measure says that Holiday Inn is not as important/influential as Airbnb or bchesky
PageRank	30.45	17.70	2.22	384.44	A variant of eigenvector centrality	holidayinn has the highest score, much higher than the rest, which means within its network holidayinn is estimated to be highly important

Clustering Coefficient	0.0046	0.008	0.1000	0.0004	Ratio that shows how connected (dense) a specific actor’s neighbors are to one another.	As actor, Airbnb, bchesky and brianchesky have neighbors with more connected one to the other compared to holidayinn

Figure 2.
Airbnb and Holiday Inn Twitter Networks Graphs

Airbnb



Holiday Inn

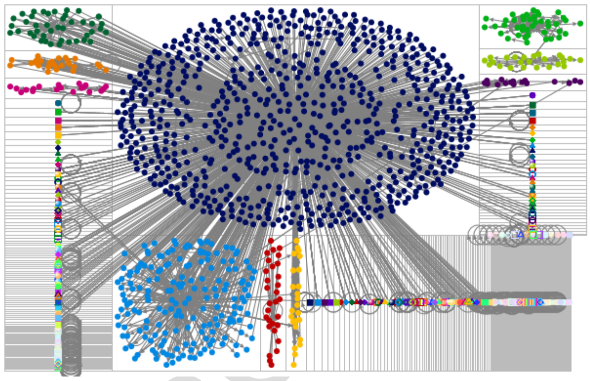


Table 4.

Tweets Profile

Service	Total tweets	URL (%)	Hashtag (%)	@ (%)	RT (%)
Holiday Inn	4141	1776/4141 (42%)	1540/4141 (37%)	1233/4141 (29%)	1144/4141 (27%)
Airbnb	1148	497/1148 (43%)	646/1148 (56%)	113/1148 (10%)	514/1148 (45%)

Table 5.
Top Hashtag Analysis

Airbnb		Holiday Inn	
Top hashtags in tweet in entire graph	Count	Top hashtags in tweet in entire graph	Count
Canneslions	185	holidayinn	325
Airbnb	81	joyoftravel	245
Mecatcannes	34	mplusplaces	83
Ogilvycannes	29	summer	70
Tbwacannes	11	ad	60
Brianchesky	10	fathersday	57
Cannesmm	8	kenbizexpo	41
Yrcannes	8	hotel	38
Travel	8	beachside	35
Startup	7	hotels	32
Airbnb was second top hashtag with portion of 21% of total top hashtags, indicating that member actors play bigger role in Twitter mwom than Airbnb itself		Holiday Inn was top hashtag with portion of 33% of total top hashtags, indicating holiday inn has bigger share compared to Airbnb in Twitter mwom marketing communication	

Table 6.
Top Replied-to Analysis

Airbnb		Holiday Inn	
Top replied-to in entire graph	Count	Top replied-to in entire graph	Count
Airbnb	4	holidayinn	153
Airbnb_uk	4	ihgservice	55
joannacoles	4	kriswilliams	28
Faris	3	evophd	13
brianchesky	3	bigbikesthom	9
cysba	2	dorisweldonkaz	7
nochedeperros	2	holidayinn_ptbo	5
bchesky	2	sdonline	4
givatayimrocks	2	certanovo	4
jelosta	2	holidayinn_tux	4
The replied-to profile of Airbnb shows that Twitter mwom marketing communication was primarily among member actors rather than with Airbnb.		The replied-to profile of Holiday Inn shows that Twitter mwom marketing communication was mainly centered to Holiday Inn as focal actor.	

Table 7.
Top Mentioned Analysis

Airbnb		Holiday Inn	
Top mentioned in entire graph	Count	Top mentioned in entire graph	Count
Airbnb	207	holidayinn	1841
bchesky	112	ihgservice	53
rickking16	51	holidayinn_ptbo	46
ogilvy	27	kenilworthtrade	31
reb_life	24	soyoso	29
brianchesky	19	ihg	27
cannes_lions	17	102touchfm	21
fastcompany	17	Certanovo	21
jenfaull	13	Kriswilliams	21
thedrum	12	Shelleyskuster	19
Airbnb was top mentioned with 41.5% of all top mentioned. The finding shows that bigger share of Twitter mwom as marketing communication was conducted by and among social network members.		Holiday Inn was top mentioned with a huge 87.3% (not to include ihgservice where Holiday Inn is in) of all top mentioned. The finding shows that Twitter mwom was generated and managed mainly to and by Holiday Inn as the focal social network actor.	

Table 8.

Sentiment Analysis

	Affective Processes		Cognitive Processes		Drives		
Holiday Inn	4.69		3.67		5.47		
Airbnb	2.95		7.49		5.18		
	Posemo	Negemo	Insight	Cause	Affiliation	Achieve	Risk
Holiday Inn	3.75	0.85	0.86	0.53	2.6	0.76	0.24
Airbnb	2.06	0.83	1.55	2.44	1.22	1.21	0.82

Figure 3.
Airbnb's Semantic Network

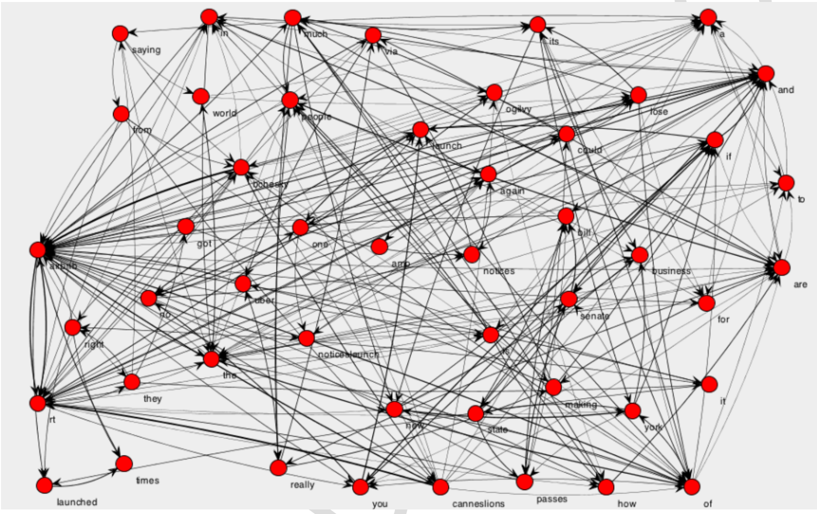
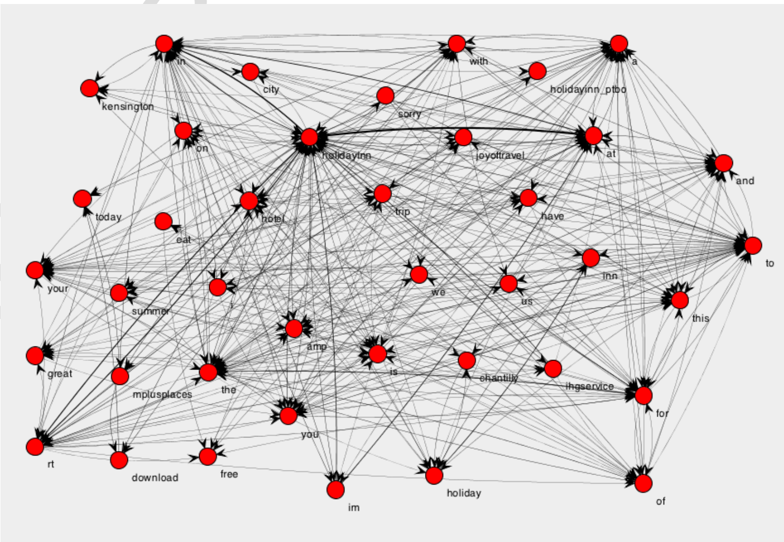


Figure 4.
Holiday Inn's Semantic Network



Highlights:

- There are five key domains of differentiation in terms of how MWOM is leveraged
- An entrepreneurial firm is network-empowering, transparent and risk-taker
- A conventional firm is more focal, controlled, risk-averse and affiliating
- An entrepreneurial firm signals offerings via network participation
- A conventional service provider signals offerings via brand orientation