BJM BRITISH JOURNAL of MANAGEMENT — BRITISH ACADEMY OF MANAGEMENT

British Journal of Management, Vol. 00, 1–19 (2024)
DOI: 10.1111/1467-8551.12829

Check for updates

The Rise of Human–Machine Collaboration: Managers' Perceptions of Leveraging Artificial Intelligence for Enhanced B2B Service Recovery

Nisreen Ameen,[1] Margherita Pagani,[2] Eleonora Pantano,[3] Jun-Hwa Cheah,[4] Shlomo Tarba[5] and Senmao Xia[6]

[1]School of Business and Management, Royal Holloway, University of London, Egham Hill, Egham, TW20 0EQ, UK, [2]SKEMA Centre for Artificial Intelligence, SKEMA Business School – Université Côte d'Azur, 5 Quai Marcel Dassault, Suresnes, 92150, France, [3]University of Bristol Business School, University of Bristol, Bristol, BS8 1SD, UK, [4]Norwich Business School, University of East Anglia, Norwich, NR4 7TJ, UK, [5]Birmingham Business School, University of Birmingham, Edgbaston Park Road, Birmingham, B15 2TY, UK, and [6]Surrey Business School, University of Surrey, Guildford, GU2 7XH, UK

Corresponding author email: xsenm6688@sina.com, s.xia@surrey.ac.uk

This research analyses managers' perceptions of the multiple types of artificial intelligence (AI) required at each stage of the business-to-business (B2B) service recovery journey for successful human–AI collaboration in this context. Study 1 is an exploratory study that identifies managers' perceptions of the main stages of a B2B service recovery journey based on human–AI collaboration and the corresponding roles of the human–AI collaboration at each stage. Study 2 provides an empirical examination of the proposed theoretical framework to identify the specific types of intelligence required by AI to enhance performance in each stage of B2B service recovery, based on managers' perceptions. Our findings show that the prediction stage benefits from collaborations involving processing-speed and visual-spatial AI. The detection stage requires logic-mathematical, social and processing-speed AI. The recovery stage requires logic-mathematical, social, verbal-linguistic and processing-speed AI. The post-recovery stage calls for logic-mathematical, social, verbal-linguistic and processing-speed AI.

Dedicated to Renaud Champion

Introduction

The field of artificial intelligence (AI), particularly generative AI, has captured considerable interest in the realm of service and management research (Brown *et al.*, 2024). This can be attributed to the remarkable advancements in computing power, lower computing costs and the development of computational abilities (Ameen *et al.*, 2022; Gupta, Wang and Czinkota, 2023; Hajli *et al.*, 2022; Nguyen and Malik, 2022). These factors have contributed to the burgeoning popularity and significance of AI in shaping the landscape of service-related studies. AI uses machine learning algorithms to mimic the human brain's cognitive processes and act accordingly. Indeed, AI aims to reproduce human abilities such as learning, speech (language processing) and problem-solving (Russell and Norvig, 2009). Moreover, the development of quantum computing and generative AI marks a leap forward in processing capability, with massive performance increases for specific uses (Ameen, Sharma and Tarba, 2024).

Although the literature offers several classifications and applications of AI in service settings, it has paid limited attention to the collaboration between AI and humans in organizations (Huang and Rust, 2022). Huang and Rust (2018) specified four ordinal and parallel types of intelligence – mechanical, analytical, intuitive and empathetic – and identified the ways firms can decide between humans and machines to provide services across the four intelligences. Pantano and Scarpi (2022) extended this classification by postulating five different types of AI more reflective of human intelligence: logic-mathematical, social, verbal-linguistic, processing-speed and visual-spatial.

Given that the research on service recovery primarily focuses on business-to-consumer (B2C) contexts (Baliga *et al.*, 2021; Grégoire and Mattila, 2021), there

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.
This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

is a significant gap in understanding service recovery in business-to-business (B2B) contexts. Moreover, in the limited body of research delving into service recovery solutions within B2B settings, the predominant focus has been on the efficacy of human agents in achieving satisfactory outcomes (e.g. Ahmad *et al.*, 2022; Baliga *et al.*, 2021; Chugh *et al.*, 2023; Grégoire and Mattila, 2021). Despite these efforts, there exists a noticeable research gap pertaining to an in-depth exploration of the ways in which various forms of AI intelligence can enhance B2B service recovery.

Both scholars and practitioners face the challenge of determining whether, when and how AI systems can substitute for or collaborate with humans in specific functions within the B2B service recovery process. Exploring these configurations may enhance the quality of B2B service recovery and improve overall efficiency.

Using AI-based technologies to manage B2B service recovery is possibly the best option for survival and for developing more resilient, sustainable recovery models. It may also cost firms less in terms of resources (human and financial) and time. In addition, AI systems can replace humans in some rote tasks (Pagani and Champion, 2020) and free up time for more advanced layers of service recovery. Nonetheless, in B2B contexts, human input remains essential for successful service recovery (Baliga *et al.*, 2021).

Service recovery in B2B contexts presents unique challenges. Compared with B2C contexts, the risks associated with service failure and inadequate recovery are far more serious and costly (Baliga *et al.*, 2021; Grégoire and Mattila, 2021). In B2B markets, a service failure can have a domino effect, impacting the entire value network ecosystem, whereas B2C service failures often affect individual customers only (Zhu and Zolkiewski, 2015). In addition, B2B purchases involve complex processes and multiple service needs, making recovery more intricate (Baliga *et al.*, 2021). Losing even a single client due to a service failure can result in substantial losses for B2B firms. Thus, effective B2B service recovery is crucial for maintaining a positive reputation and long-term client relationships while minimizing costs.

Although previous studies have proposed research questions on collaborations between humans and AI (Bond *et al.*, 2020; Huang and Rust, 2022), research has yet to provide insight into managers' perceptions of how the collaboration between human intelligence and AI intelligence can be used effectively in each stage of B2B service recovery. Therefore, in this research, we consider B2B service recovery as a journey made up of different stages. We note that it is still unknown how different AI intelligence can be combined and used effectively at each stage of the B2B service recovery journey. This research aims to develop a theoretical framework that identifies which types of AI intelligence are significant at each stage of the B2B service recovery journey, based on managers' perceptions, thus enabling successful human–AI collaboration in this context.

This research contributes to theory in several ways. First, it extends the theory of intelligence (Huang and Rust, 2018) and an AI collaborative intelligence framework for marketing tasks (Huang and Rust, 2022); it also provides empirical evidence to extend previous research on B2B service recovery (e.g. Ashok, Day and Narula, 2018; Baliga *et al.*, 2021; Brock *et al.*, 2013; Naumann *et al.*, 2010; Zhu and Zolkiewski, 2015). It answers recent calls to develop methods of collaboration between AI and humans in organizations (Ameen *et al.*, 2022; Bond *et al.*, 2020; Huang and Rust, 2018, 2022; Pantano and Scarpi, 2022) and extends these studies by offering empirical evidence for how humans and AI can collaborate effectively at each stage of the B2B service recovery journey (Van Vaerenbergh *et al.*, 2019), a context in which the integration of AI is still underexplored (see Table 1). It proposes a theoretical model that goes beyond traditional theories in B2B service recovery, such as justice theory and attribution theory, thereby providing a new perspective for understanding human–AI collaboration based on managers' insights. Secondly, this research provides an innovative approach that firms from different industries can use to manage B2B service recovery, which is a costly and risky endeavour (Baliga *et al.*, 2021). Thirdly, we identify four main stages of the B2B service recovery journey – *prediction*, *detection*, *recovery* and *post-recovery* – and demonstrate how five types of AI intelligence (logic-mathematical, social, verbal-linguistic, processing-speed and visual-spatial) can be combined to perform key tasks. Fourthly, our study extends the research on AI (e.g. Ameen *et al.*, 2022; Huang and Rust, 2018; Pantano and Scarpi, 2022) beyond the scope of B2C contexts. Indeed, the business relevance of this paper lies in the fact that in B2B service recovery, firms need effective strategies to minimize costly financial and reputational risks and enhance their performance.

Theoretical background

Service recovery management in B2B contexts

Service failure is defined as 'any type of error, mistake, deficiency or problem that occurs during the provision of a service, causing a delay or hindrance in the satisfaction of customer needs' (Koc, 2017, p. 1). When a service failure occurs, customer attributions and expectations are shaped by relationship factors and are associated with greater satisfaction with the service performance after the recovery (Hess, Ganesan and Klein, 2003).

Service outcome failures are more common in B2B contexts than in B2C contexts (Baliga *et al.*, 2021). They

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 1. Recent studies on B2B service recovery

Reference	Brief description (in context of B2B service recovery)	Underlying theory	Inclusion of AI role
Brock *et al.* (2013)	Drivers of client satisfaction with complaint handling	• Justice	No
Zhu and Zolkiewski (2015)	B2B service failures in manufacturing	• –	No
Ashok, Day and Narula (2018)	Clients' dissatisfaction and service process innovation	• Expectation disconfirmation	No
Van Vaerenbergh *et al.* (2019)	Service recovery journey	• Social exchange	Yes
Khamitov, Grégoire and Suri (2020)	Brand transgression, service failure and recovery, and product-harm crisis	• Attribution • Justice • Expectation disconfirmation • Relationship marketing	No
Baliga *et al.* (2021)	Service failure and recovery in B2B markets	• Justice	No
Grégoire and Mattila (2021)	Review of the literature on service failure and recovery	• Justice • Attribution • Game	No
Ahmad *et al.* (2022)	Salesforce control system on service–sales ambidexterity and service-related performance outcomes	• Motivation, opportunity and ability (MOA)	No
Chang (2022)	The infusion of AI in B2B sales	• Relationship lifecycle • AI job replacement	Yes
Sands *et al.* (2022)	Industrial customer engagement in customer responses to service failure	• Social exchange	No
Chugh *et al.* (2023)	Purchasing agents' termination emotions on their perception of justice towards an existing win-back offer, and their advocacy towards switching back to this supplier	• Constructed emotion • Justice	No

cause clients to experience financial losses and are often highly dependent on the firms' responsiveness and how effectively they recover the failure. Hence, supplier quality and timeliness of delivery are crucial (Sands *et al.*, 2022). In the context of B2B services, the cause and severity of a failure have implications for the recovery mechanism deployed, and the solution may be associated with the age and size of the firm, the size of the client, and the length and strength of the relationship between the two (Baliga *et al.*, 2021).

Recent research acknowledges that major global developments have made B2B service recovery more challenging for firms (Bond *et al.*, 2020). For instance, the easy availability of competitive offerings has led to hyper-competition in B2B markets (Baliga *et al.*, 2021). In addition, clients increasingly expect personalized, frictionless experiences and expect firms to monitor their performance in real time to predict failure and take timely action to prevent it (Shin *et al.*, 2017). When a failure does happen, the reactions of B2B customers vary from tolerance and continuing to use the supplier, to defection (Naumann *et al.*, 2010). Furthermore, rapid advances in technology have led to demand among B2B customers for digital self-service systems, supported by AI and automation, so they can resolve smaller issues whenever and wherever they want (Baliga *et al.*, 2021). Hence, finding new forms of AI-enabled solutions that help firms predict, detect and possibly avoid B2B service failures, in addition to aiding with the actual recovery, is essential in today's world.

Furthermore, service recovery should be treated as a journey (Van Vaerenbergh *et al.*, 2019). This journey comprises a series of events in the pre-recovery, recovery and post-recovery phases, which collectively shape the recovery experience. Van Vaerenbergh *et al.* (2019) explain that viewing service recovery as a journey allows us to consider the dynamics of the service process and better understand the customer's viewpoint over time; it goes beyond a momentary snapshot that ignores touchpoint dependencies, enabling firms to manage the service recovery process holistically.

We note that there has been a surge in research on the role of AI in service contexts (e.g. Ameen *et al.*, 2022; Huang and Rust, 2018, 2022; Pantano and Scarpi, 2022). For example, Luo *et al.* (2021) found that AI–human coach assemblage outperforms either the AI or human coach alone, while Habel, Alavi and Heinitz (2023) found that the effectiveness of AI-based churn prediction strongly depends on customer and salesperson characteristics, including technology perceptions. Table 1 presents an overview of the most recent studies on B2B service recovery. We note that there remains a lack of exploration and empirical assessment on how the collaboration between AI and human intelligence can enhance firms' B2B service recovery performance.

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Overview of the studies

Our research comprises two studies aimed at identifying the types of AI intelligence required at various stages of the B2B service recovery journey for successful human–AI collaboration in this context. Initially, we conducted Study 1, a qualitative exploratory study based on data collected from senior managers to explore (i) the main stages of a human–AI collaboration-based B2B service recovery journey and (ii) the specific collaborations between humans and AI at each stage. Building upon these findings, Study 2 empirically tested our proposed theoretical framework by examining managers' perceptions of the impact of the specific types of AI on B2B service recovery performance from managers' perspectives at each stage of the service recovery journey. The results contribute to the understanding of effective human–AI collaboration in service contexts.

Study 1: Exploratory study

The exploratory qualitative study aimed to capture a comprehensive understanding of the role of AI in B2B service recovery. Specifically, the study (i) investigates the main stages of a B2B service recovery journey based on human–AI collaboration and (ii) explores the collaboration between humans and AI at different stages of the journey. Given the limited research available on the collaboration between humans and AI in B2B service recovery, this study employed in-depth interviews with senior managers and industry experts to shed light on this important topic.

Procedure

We conducted interviews with individuals who were experienced in generating, developing and implementing B2B service recovery solutions based on human–AI collaboration. Of the ten participants, nine were senior managers from leading global firms (NVIDIA, IBM, Microsoft, Tag Digital, Vertis Media, Zebra Technologies and Parallel Dots). These firms offer AI-enabled B2B services in marketing, retail, warehousing and information technology. The remaining participant was an industry expert specializing in AI and robotics in 4.0 logistics, security and health (Web Appendix A). We used a judgement sampling technique to select the participants and conducted the interviews online. All participants were highly involved in planning and managing AI in B2B service recovery. We used a semi-structured interview format and began each interview with a concise explanation of the study's objectives. We asked open-ended questions to explore aspects related to B2B service recovery: how teams and AI identify and handle service failures; the stages of B2B service recovery; the role and types of AI-enabled technologies used in handling and recovering service disruptions/problems; important factors in B2B service recovery; and the future use of AI in service recovery. Prior to conducting the interviews, we obtained ethical approval from the lead researcher's university. The average interview length was 40 min. We developed the interview questions based on a thorough review of online reports and literature on the service recovery journey and human–AI collaboration (e.g. Baliga *et al.*, 2021; Huang and Rust, 2022; Pantano and Scarpi, 2022; Van Vaerenbergh *et al.*, 2019).

Following the interviews, the recordings were transcribed verbatim. Two of the authors then analysed the data using a commonly accepted analysis technique involving open and axial coding (Strauss and Corbin, 1998). This coding approach facilitated the identification of common themes and patterns in the data. The researchers examined similarities and patterns within each interview and across all the interview texts. We then used dialectical tracking to compare these patterns with existing conceptualizations in the literature (Belk, Fischer and Kozinets, 2013). We ran further analysis of the verbatim transcripts using WordStat software, which allowed us to combine qualitative and quantitative analysis techniques for a better understanding of the interview data. Specifically, the functions of automatic frequency analysis of words, co-occurrences and proximity plots embedded in software allowed us to identify key insights and emerging themes related to human–AI collaboration in B2B service recovery.

Findings

To support deep understanding of the interviews, we performed a preliminary frequency analysis and a co-occurrence analysis on the most recurrent words (Web Appendix B) using WordStat. This analysis was limited to the cluster that contains a large number of interconnected words. This initial analysis allowed us to understand the extent to which a couple of words recurred to have an overview of the recurrent associations of words, while the subsequent proximity plot provided a deeper analysis of the frequency of the word 'AI' only in association with other words (Web Appendix B). The results of both analyses helped us to extract from the most recurrent concepts. For instance, the role of AI in detection largely emerged (e.g. from the co-occurrences analyses, 'AI' frequently occurred with words like 'detect' and 'detection', while 'service' occurred frequently with 'failure' and 'disruption'; from the proximity plot we further see the large frequency of 'AI' with 'service'). The findings of this exploratory study form the basis of the research and the proposed hypotheses, along with the literature. The participants stressed that AI involvement in B2B service recovery is important, because it can handle tasks that may be

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

challenging for humans. They highlighted integrating machine learning algorithms into the service recovery process as a way of enhancing efficiency and effectiveness. However, participants also emphasized the need for human intervention to meet clients' specific needs. For instance, one senior manager stated:

> The use of AI can detect very early a change in plans and behaviours and identify breach as opposed to the breaches happened and how you contain the breach. So there are literally hundreds of thousands of use cases. It's really difficult to say 'well, which one?' because there are, there are hundreds of thousands. [P1]

Managers described their approach to using AI in B2B service recovery. A senior manager explained:

> We have some module which is a nicer module or a self-healing or recovery that can be triggered. It follows a set of paths. Very obvious one would be restart that service or change this input and then it does that so and then how would you know about that. [P6]

The interview data analysis revealed that a B2B service recovery journey based on human–AI collaboration consists of four main stages: (i) *prediction*, (ii) *detection*, (iii) *recovery*; and (iv) *post-recovery* (Table 2).

In summary, the findings of this exploratory study align with, and contribute to, the literature on the main stages of human–AI collaboration in B2B service recovery (Van Vaerenbergh *et al.*, 2019). In emphasizing the importance of human–AI collaboration at each of the four stages, the findings complement those of other studies (e.g. Baliga *et al.*, 2021; Huang and Rust, 2022; Pantano and Scarpi, 2022) and add to the body of knowledge on human–AI collaboration in service contexts.

Conceptual framework and hypothesis development

Recent service and marketing research has emphasized that firms can achieve the best results through augmentation, which involves collaborations and combinations of AI and human intelligence (Ameen *et al.*, 2022; Huang and Rust, 2018, 2022; Pantano and Scarpi, 2022). These studies provided insights into how collaborative intelligence can address the crucial issue of leveraging AI to augment human intelligence at different levels. Huang and Rust (2022) proposed the theory of human–AI collaboration, which suggests that successful collaboration between AI and human intelligence can be achieved by recognizing their respective strengths. In this way, lower-level AI augments higher-level human intelligence, enabling human intelligence to advance at a higher level as AI automates lower-level tasks (Huang and Rust, 2022). Pantano and Scarpi (2022) identified five main AI intelligence types: *logic-mathematical*, *social*, *visual-spatial*, *verbal-linguistic* and *processing-speed*, each corresponding to different aspects of human intelligence. Table 3 provides a detailed description of each type of intelligence.

However, a gap remains in understanding what role the different AI intelligence types play in B2B service recovery. Van Vaerenbergh *et al.* (2019) noted that AI applications can provide real-time support to the service frontline, which assists service organizations in their recovery efforts. Furthermore, recent research has emphasized three main stages in the service recovery journey: pre-recovery, during recovery and post-recovery (Grégoire and Mattila, 2021; Van Vaerenbergh *et al.*, 2019). Nevertheless, there is no precise definition or understanding of these stages in the B2B service recovery journey when AI is involved. To address these gaps, this research expands the theory of AI–human collaborative intelligence (Huang and Rust, 2022) with empirical evidence. We propose a theoretical framework of AI intelligence types and their significance at various stages of the B2B service recovery journey, ultimately enhancing service recovery performance. By doing so, this research aims to provide academics, marketers and practitioners with more accurate solutions to challenges in B2B service recovery contexts. Figure 1 presents the proposed theoretical framework.

Logic-mathematical AI enables machines to tackle complex analytical problems and make logical decisions (Huang and Rust, 2018; Pantano and Scarpi, 2022). This form of intelligence, akin to human intelligence, encompasses the capacity to analyse problems and situations logically before identifying appropriate solutions, and it is relevant to different stages of the B2B service recovery journey. The ability to make logical decisions when identifying B2B service errors and generating solutions during service recovery is critical in fostering positive relationships between B2B clients and service providers (Sands *et al.*, 2022). This AI intelligence type holds particular significance in the B2B service recovery journey due to the inherent complexity and severity of the failures that may occur (Baliga *et al.*, 2021). For instance, in the realm of smart B2B services, failures can manifest as bugs in automated B2B platforms or the abrupt cessation of functionality without any clear cause.

Processing-speed AI encompasses the machine's ability to perform repetitive tasks quickly and fluently, drawing upon the Cattel–Horn–Carroll model of human intelligence (Schneider and McGrew, 2012). In the context of B2B service recovery, processing-speed AI is significant as clients expect real-time performance monitoring of products and services provided, so that failures can be anticipated and timely corrective action can be taken (Baliga *et al.*, 2021; Shin *et al.*, 2017). This type of AI can be required in all stages

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 2. Exploratory study findings: collaboration between humans and AI by stage of service recovery

Stage: Description	Example AI systems	Machine role	Human role
1. **Prediction**: Machine learning algorithms and predictive analytics are employed to analyse customer data and predict potential failures. Humans play a crucial role in collecting relevant data, training AI models and defining key performance indicators for measuring the effectiveness of the service recovery process.	• Machine learning systems • Predictive analytics systems	AI systems cross several variables to predict service failure. Predictive analytics systems can analyse customer data to predict potential issues before they occur. By identifying patterns in customer behaviour, these systems can alert businesses to potential service failures and help them take action to prevent them.	Humans provide the necessary input data for the AI system and ensure the accuracy and effectiveness of the predictions generated. Humans identify and collect relevant data for training the AI model and ensure that the data is accurate and representative of the target population. Humans work with the AI system to identify key performance indicators (KPIs) for measuring the effectiveness of the service recovery process. These KPIs could include metrics such as response time, customer satisfaction levels and resolution rate. Humans collaborate with the AI system to develop and refine prediction models that can accurately predict customer needs and preferences. This may involve testing and validating different models and making adjustments based on feedback and results.
2. **Detection**: Various AI systems – including natural language processing (NLP), speech recognition, predictive analytics, machine learning and chatbots – are used to identify failures (i.e. by detecting customer sentiment, analysing the tone and emotion in the customer's voice and identifying anomalies in customer behaviour) and suggest potential solutions. Humans are needed for monitoring, decision-making, personalizing, showing empathy and continuously improving AI systems.	• NLP systems • Speech recognition systems • Machine learning systems • Chatbots	NLP systems can detect customer sentiment and intent from emails, chat logs and social media posts. By analysing the language used, NLP systems can identify customer complaints, errors and faults in the system and highlight areas where service recovery may be needed. Speech recognition systems can transcribe customer calls and analyse the tone and emotion in the customer's voice. This can help firms detect customer frustration or dissatisfaction and trigger service recovery measures. Machine learning systems can be trained to identify anomalies in customer behaviour and patterns that indicate a need for service recovery. For example, a machine learning system could be trained to detect when a customer is repeatedly attempting to perform a specific action on a website, indicating a potential problem.	Monitoring and oversight: Humans need to monitor AI systems and ensure they are operating correctly. They can also provide oversight and review the results generated by AI systems to ensure they are accurate and reliable.

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 2. (Continued)

Stage: Description	Example AI systems	Machine role	Human role
3. **Service recovery**: AI systems – including recommendation engines, predictive analytics systems, NLP, sentiment analysis, chatbots and, more recently, ChatGPT – are employed to provide personalized solutions, assist immediately, proactively resolve issues and analyse customer feedback. Humans address specific cases, provide empathy and find individualized solutions when needed.	• Recommendation engines • Chatbots • Predictive analytics systems • NLP systems • Sentiment analysis systems • ChatGPT	Recommendation engines can suggest personalized solutions to customers based on their previous behaviour, preferences and history with the firm. For example, if a customer has purchased a certain product or service before, a recommendation engine could suggest a related product or service as a solution to their current issue. Chatbots can provide immediate assistance to customers during the recovery process. They can answer common questions, provide guidance on next steps and escalate issues to a human support agent if necessary. Predictive analytics systems can identify potential future issues and address them before they become bigger problems. For example, if a customer has a history of experiencing a certain issue, a predictive analytics system could alert the firm to take preventative measures to avoid the issue occurring again. NLP systems can analyse customer feedback and identify patterns or trends in customer complaints. This can help firms identify the root cause of issues and target improvements to prevent similar issues from occurring. Sentiment analysis systems can analyse customer feedback and determine the overall sentiment of customers towards the firm. This can help firms identify areas for improvement and tailor their recovery efforts to specific concerns.	Humans address specific cases and situations, finding an individual solution and adding empathy. Humans can also address more difficult questions, specific issues and tailored solutions that chatbots cannot deal with in an automated way. Decision-making: Humans are ultimately responsible for making decisions about which AI-recommended action to take. Humans can consider factors that AI systems might not consider, such as the overall business strategy or customer relationship considerations. Personalization and empathy: AI systems may be able to detect issues and provide solutions, but humans are better equipped to provide a personalized response that considers the unique needs of each customer. Humans can also provide empathy and emotional support to customers who are experiencing service issues, which is difficult for AI systems to replicate.
4. **Post-recovery**: Predictive analytics, chatbots and report analysis are used to identify patterns and trends, prevent similar issues in the future and analyse customer feedback once the recovery process is complete. Humans follow up with customers to ensure satisfaction, monitor AI system performance and use customer feedback to adjust, develop and enhance the service recovery process. Participants also noted that the size of the business client and the length of the relationship can influence the use of AI in B2B service recovery.	• Predictive analytics • Report analysis • Chatbots	Predictive analytics systems can analyse data from the recovery process and identify patterns or trends that can be used to predict and prevent similar issues in the future. For example, if a certain product or service is frequently associated with customer complaints, a predictive analytics system could identify this pattern and suggest improvements to that product or service to prevent future issues. NLP systems can analyse customer feedback and identify areas for improvement in the overall service delivery process. For example, if customers frequently complain about a particular aspect of the service, such as response times or communication, an NLP system could identify this pattern and suggest improvements. Chatbots can gather feedback from customers after the recovery process is completed. Firms can use this feedback to identify areas for improvement and inform future service delivery strategies.	Humans have to follow up with customers to ensure that the issue is fully resolved and that they are satisfied with the outcome (reaching out to customers by phone, email or automated surveys). Humans have to monitor the performance of the AI system and adjust it as needed. This could include analysing customer feedback to identify areas of improvement, check the accuracy of the model or address technical issues. Humans undergo ongoing training and development to explore new technologies and tools to enhance the service provided. Humans play a critical role in continuously improving AI systems. They can provide feedback and make adjustments to improve the accuracy and effectiveness of AI systems over time.

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 3. Descriptions of AI intelligence type

Type of intelligence	Description
Logic-mathematical AI	Logic-mathematical AI is especially important in identifying and resolving service problems in this context, given that B2B clients expect problems to be resolved efficiently to minimize their (financial and non-financial) losses (Baliga *et al.*, 2021). Specialized mathematical algorithms, which extract patterns from vast amounts of data, allow AI systems to perform computationally intensive tasks (such as classification and regression) more proficiently than humans can (Esmaeilzadeh and Vaezi, 2022).
Processing-speed AI	The processing-speed type of intelligence focuses on performing simple and repetitive tasks quickly and fluently without overlapping with other forms of intelligence, such as logic-mathematical, visual-spatial or verbal-linguistic (Pantano and Scarpi, 2022). It also includes mechanical intelligence, which pertains to the execution of basic and repetitive tasks (Huang and Rust, 2018, 2021). As Huang and Rust (2018) elucidate, mechanical processes in humans do not require much creativity, as the processes have been performed repeatedly and can be executed with minimal additional cognitive effort. AI possesses the inherent advantage of extreme consistency (Huang and Rust, 2018, 2022). The repetitive nature of tasks characterized by limited variation diminishes the value of learning over time, instead relying on observation to repetitively act and react (Huang and Rust 2018).
Social AI	Social AI is centred on machines' ability to understand human emotions, respond to social cues and interact with humans. AI can employ a holistic and contextually integrated approach to learn and adapt from experience and contextual factors. It can analyse emotional cues, such as facial expressions, smiling, anger or fear (Puntoni *et al.*, 2021). While this type of intelligence holds significance in frontline interactions between clients and AI in service settings, it also plays a crucial role in back-end support. Empathetic AI applications can provide emotional analytics for improving customer experience and engagement (Esmaeilzadeh and Vaezi, 2022). For instance, by analysing human expressions and categorizing them into emotions such as sadness, happiness, anxiety or joy, AI can track not only what customers say but also how they truly feel (Huang and Rust, 2018). By identifying customer emotions, such AI systems enable employees to devise suitable responses and firms to deliver timely and appropriate services (Ameen *et al.*, 2022).
Verbal-linguistic AI	Verbal-linguistic AI is commonly found in chatbots or AI voice assistants, allowing them to comprehend customer complaints in the context of a service failure and provide appropriate responses (Fotheringham and Wiles, 2023; Grégoire and Mattila, 2021; Pizzi, Scarpi and Pantano, 2021).
Visual-spatial AI	Visual-spatial AI is based on a machine's understanding of space and spatial awareness, enabling it to analyse patterns, navigate physical environments and manipulate objects (Pantano and Scarpi, 2022; Solomon and Lo, 2022).

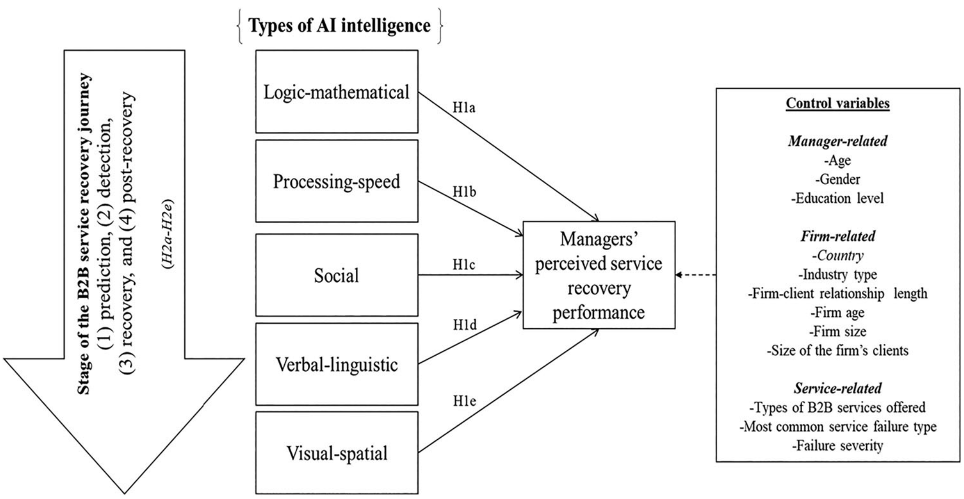

Figure 1. Conceptual model

of the B2B service recovery journey. For instance, AI can swiftly predict and detect common failures and problems through machine learning and predictive analytics. Furthermore, AI can expediently handle common complaints from B2B clients regarding simple failures (such as delayed delivery) while ensuring that customers are satisfied with the outcome. Moreover, once a B2B service failure has been recovered, AI can assist the service provider by gathering information about recurring failures and generating reports that can be used to prevent such failures in the future.

Social AI pertains to a machine's capacity to engage in social interactions and display empathetic behaviour in various contexts (Esmaeilzadeh and Vaezi, 2022; Huang and Rust, 2018; Pantano and Scarpi, 2022). We argue that social AI is particularly important in the context of service failure, because customers' emotions – including anger, fear of loss and sadness – play a significant role during and after the recovery process, which influences their relationship with the firm. However, the literature presents contrasting perspectives on the role of emotions in B2B service recovery. B2B interactions

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

involve more complex decision-making than B2C interactions do, and they are influenced by multiple actors simultaneously (e.g. Kranzbühler *et al.*, 2020). It is often argued that emotions are less prominent in professional settings than in end-consumer scenarios, because organizational buying is primarily driven by logic and reason (e.g. Webster, Trevino and Ryan, 1993). It is also argued that emotions and empathy are pivotal in the context of B2B service failure and recovery, because negative emotions between firms can lead to retaliatory actions extending beyond a specific exchange failure (Chugh *et al.*, 2023).

Verbal-linguistic AI refers to a machine's ability to understand and simulate human language, enabling interactions through spoken or written language (Pantano and Scarpi, 2022). In the B2B context, where operational efficiency is prioritized, integrating verbal-linguistic AI into service recovery can enhance customer satisfaction (Fotheringham and Wiles, 2023). For instance, it gives chatbots the advantages of personalization and contextualization (Ameen *et al.*, 2022). Finally, in the context of service recovery, visual-spatial AI can be applied to tasks such as locating delayed orders or solving inventory management problems (Pantano and Scarpi, 2022). By leveraging this intelligence type, AI can detect spatial relationships and patterns in data, which provides valuable insights for effective decision-making. Nevertheless, each intelligence type is equally relevant for the machine, as for the humans (Gardner, 1983), and having one intelligence over another does not make the human or the machine 'more intelligent'. Thus, for instance, processing speed (Pantano and Scarpi, 2022) and mechanical intelligence (Huang and Rust, 2018, 2021) play the same role of a different type of intelligence in the overall 'intelligence' of the machine and vice versa. Therefore, we propose the following hypothesis:

H1:Logic-mathematical (a), processing-speed (b), social (c), verbal-linguistic (d) and visual-spatial (e) AI intelligence has a significant effect on managers' perceived service recovery performance across all stages of the B2B service recovery journey.

The B2B service recovery journey, as outlined by Huang and Rust (2018, 2022) and Rust and Huang (2021), involves distinct stages, each demanding specific AI intelligences. Furthermore, in line with the views reported in previous studies (e.g. Grégoire and Mattila, 2021; Van Vaerenbergh *et al.*, 2019), the B2B service recovery journey consists of multiple stages, namely: prediction, detection, recovery and post-recovery, each requiring specific skills and intelligences from both AI and humans. In addition to the direct effects, we propose that the five types of AI intelligence vary in terms of their significance at each of the four stages of the B2B service recovery journey. We explain this view with support from the existing literature as well as Study 1 results.

We expect that at the *prediction* stage of the B2B service recovery journey, both *processing-speed* and *visual-spatial AI* can play a significant role. Processing-speed AI can serve at this stage of the B2B service recovery by enabling data-driven predictions. This type of AI, empowered by machine learning algorithms, can analyse vast amounts of historical data (e.g. service records, customer complaints, sensor data) and identify patterns and correlations that signal impending failures. This enables proactive interventions and prevents service disruptions (Pantano and Scarpi, 2022). In addition, the processing speed allows real-time monitoring as AI algorithms can continuously monitor key metrics (e.g. system performance, equipment readings, customer sentiment) in real time to predict possible B2B service failures. This rapid identification of potential issues allows for swift corrective actions, minimizing the possibility of service failures (Habbal, Ali and Abuzaraida, 2024). In addition, AI can be trained to identify deviations from established baselines in data patterns. This helps pinpoint anomalies that may indicate potential service issues before they escalate, enabling preventative measures.

In addition, visual-spatial AI can play a significant role in the prediction stage of the B2B service recovery journey. Visual-spatial AI allows predictive maintenance as computer vision technologies powered by visual-spatial AI can analyse images and videos of equipment or infrastructure to identify early signs of wear and tear or potential malfunctions (Pantano and Scarpi, 2022). This proactive approach to identifying failures allows for scheduled maintenance before breakdowns occur, minimizing service disruptions (Surendran, Khalaf and Tavera Romero, 2022). In addition, this type of AI intelligence can allow remote visual inspection, for example, augmented and virtual-reality technologies supported by visual-spatial AI can enable remote technicians to virtually 'enter' customer environments and conduct visual inspections of equipment or infrastructure. This allows for early detection of potential issues without the need for physical visits, leading to faster response times and preventative actions. Furthermore, visual-spatial AI allows sensor data visualization as this type of AI intelligence can create informative visualizations of sensor data from equipment or systems. This helps human experts identify subtle trends and patterns that may indicate an increased risk of failure, enabling proactive measures.

Processing-speed AI and visual-spatial AI offer significant potential for predicting B2B service failures, each with unique strengths. Their combined application can create a more accurate, real-time and proactive approach to preventing service disruptions, increasing customer satisfaction and reducing costs (as found in the

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Study 1 results), due to the ability to quickly process a larger amount of instances than humans.

In addition, we predict that at the *detection* stage of the B2B service recovery journey, *processing-speed*, *logic-mathematical* and *social AI* can play a significant role. Processing-speed AI allows real-time data monitoring. This type of AI, fuelled by machine learning algorithms, excels at analysing vast amounts of real-time data streams (e.g. operational metrics, customer interactions, social media mentions) (Ameen *et al.*, 2022). Through pattern recognition and anomaly detection, these algorithms can rapidly identify deviations from normal service behaviour, signalling potential failures before they escalate (Ameen, Sharma and Tarba, 2024; Habbal, Ali and Abuzaraida, 2024). In addition, this type of AI allows predictive maintenance by analysing sensor data and historical maintenance records, hence it can predict equipment failures and service disruptions before they occur (Ameen *et al.*, 2022). This enables proactive maintenance interventions, minimizing downtime and associated costs. The processing-speed type of AI scales efficiently with data volume, allowing for widespread deployment across complex B2B service settings. Its automated nature helps businesses overcome human limitations in processing large amounts of data, leading to faster and more consistent detection of service failures (Lv *et al.*, 2022; Suhaili, Salim and Jambli, 2021).

Logic-mathematical AI is also required at the detection stage as it allows root cause analysis. This type of AI, powered by rule-based systems and reasoning algorithms, excels at analysing complex relationships and logical dependencies within datasets (Sarker, 2021). This allows for in-depth root cause analysis of service failures, pinpointing the specific factors and interactions that led to the issue (Surendran, Khalaf and Tavera Romero, 2022). It also offers scenario modelling and simulation as it can create predictive models and simulations of various service scenarios. This enables proactive identification of potential failure points and vulnerabilities within service systems, leading to preventative measures and improved service design (Habbal, Ali and Abuzaraida, 2024). Furthermore, this type of AI allows customization. Logic-mathematical AI models can be tailored to specific B2B service contexts and industry standards. Additionally, their rule-based nature provides explainable insights into the detection process, facilitating human understanding and trust in the system's recommendations (Anvar Shathik and Krishna Prasad, 2020; Jain, Pamula and Srivastava, 2021).

Social AI can play a significant role in detecting B2B service faults through early detection as it can detect issues in real time, minimizing the negative impact of service failures. Early intervention reduces customer frustration and allows for quicker recovery efforts (Ameen, Viglia and Altinay, 2023). In addition, it enables proactive identification as it allows performing sentiment analysis, which can identify potential dissatisfaction even before explicit complaints emerge (Agnihotri and Bhattacharya, 2024). This enables proactive outreach and prevents minor issues from escalating, which is particularly significant in the B2B context where maintaining a positive relationship with clients is key (Doney, Barry and Abratt, 2007). Furthermore, social AI enables richer customer insights as it analyses not just factual reports but also emotions and opinions (Liu-Thompkins, Okazaki and Li, 2022). This deeper understanding of customer perspectives informs personalized recovery strategies. In addition, social AI enables multi-channel monitoring as it can track complaints across diverse channels and communication platforms, providing a holistic view of customer sentiment.

Processing speed, logic-mathematical and social AI offer complementary tools for detecting B2B service failures. Their combined application allows for rapid identification of issues, an in-depth understanding of root causes and proactive prevention measures. This empowers businesses to minimize service disruptions, maintain customer satisfaction and enhance operational efficiency.

In addition, we predict that the *recovery* stage of the B2B service recovery journey requires logic-mathematical, social, verbal-linguistic and processing-speed AI. Logic-mathematical AI allows root cause analysis, which facilitates targeted recovery efforts by addressing the core issue and preventing future occurrences (Surendran, Khalaf and Tavera Romero, 2022). Also, this type of AI offers scenario planning and decision support as it can model various recovery scenarios based on the identified root cause and predict their potential outcomes. This empowers businesses to make informed decisions, optimize resource allocation and choose the most effective recovery strategy (Habbal, Ali and Abuzaraida, 2024). Furthermore, logic-mathematical AI offers automated workflow optimization as it can analyse historical data and recovery patterns to identify inefficiencies and bottlenecks in existing workflows. This allows for automated optimization of recovery processes, leading to faster resolutions and reduced costs (Anvar Shathik and Krishna Prasad, 2020; Jain, Pamula and Srivastava, 2021).

Social AI can also play a significant role at this stage as it supports firms by allowing sentiment analysis and emotional understanding (Chaturvedi *et al.*, 2023). Social AI tools can analyse customer communication (emails, chats, social media) to understand their emotions and sentiments regarding service failure (Ameen, Viglia and Altinay, 2023; Chaturvedi *et al.*, 2023). This allows businesses to tailor their recovery approach, offering personalized apologies, acknowledging frustrations and demonstrating empathy (Anvar Shathik and Krishna Prasad, 2020; Jain, Pamula and

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Srivastava, 2021). In addition, social AI enables building customer relationships, for example, social AI chatbots can engage with customers during the recovery process, providing updates, answering questions and offering support. This personalized interaction can rebuild trust, mitigate negative emotions and enhance customer satisfaction (Alabed, Javornik and Gregory-Smith, 2022). Social AI supports community management and reputation repair at the B2B service recovery stage. Social AI tools can monitor online conversations and identify negative mentions of service failure. By proactively addressing these concerns and mitigating reputational damage, businesses can maintain positive relationships with their B2B partners.

Verbal-linguistic AI can support firms at the recovery stage of the B2B service recovery journey through automated apologies and communication. Here, natural language processing and language generation capabilities of verbal-linguistic AI can be used to craft personalized and sincere apologies to customers (Guzman and Lewis, 2019). This demonstrates professionalism, takes responsibility for the failure and sets a positive tone for the recovery process. In addition, this type of AI allows negotiation and conflict resolution as AI-powered negotiation tools can analyse customer demands and identify mutually beneficial solutions during the recovery process. This facilitates efficient agreements, reduces friction and promotes positive relationship building (Anvar Shathik and Krishna Prasad, 2020; Jain, Pamula and Srivastava, 2021). Verbal-linguistic AI also enables personalized communication and reporting as it can generate customized reports for various stakeholders (clients, management, internal teams) detailing the service failure, recovery actions and lessons learned. This fosters transparency, accountability and continuous improvement within the organization (Lv *et al.*, 2022; Suhaili, Salim and Jambli, 2021).

Processing-speed AI can also support firms at the recovery stage by allowing real-time feedback analysis. This type of AI can analyse customer feedback during the recovery process in real time, identifying areas for improvement and gauging the effectiveness of recovery efforts. This allows for dynamic adjustments and ensures the customer remains at the centre of the repair strategy (Habbal, Ali and Abuzaraida, 2024). Also, this type of AI enables firms to conduct predictive customer churn. Advanced machine learning algorithms can analyse customer data and recovery interactions to predict the likelihood of churn. This enables proactive interventions to retain customers and mitigate further damage to relationships. Processing-speed AI allows resource optimization and allocation as it can analyse data from previous recoveries and identify the most efficient allocation of resources (e.g. personnel, communication channels) based on the specific service failure. This optimizes resource utilization and minimizes recovery costs.

Combining these four AI types in a cohesive B2B service failure recovery strategy can generate significant benefits for firms as it allows holistic understanding that can guide a multifaceted recovery approach, personalized and empathetic response and proactive and efficient recovery.

The *post-recovery* stage presents a valuable opportunity to learn, strengthen relationships and prevent future occurrences. We predict that AI can play a significant role in this phase, with four key types: *social*, *verbal-linguistic*, *logic-mathematical* and *processing-speed AI*, offering various benefits. Social AI allows B2B firms to develop customer sentiment analysis and relationship building through monitoring customer conversations post-recovery, which helps assess the effectiveness of repair efforts and identify lingering dissatisfaction. Social AI tools can analyse sentiment and emotions in feedback and interactions, informing targeted follow-up communication to rebuild trust and solidify relationships (Anvar Shathik and Krishna Prasad, 2020; Jain, Pamula and Srivastava, 2021). In addition, this type of AI allows a proactive engagement in online communities to help address any remaining negativity surrounding the service failure. Social AI can assist in identifying and responding to mentions of the incident, actively managing the brand's reputation and fostering positive narratives among B2B partners. Social AI also enables customer churn prevention and win-back strategies as it can analyse customer behaviour and communication post-recovery to identify those at risk of churn. Early detection allows for targeted retention efforts, offering personalized incentives or support to prevent customer loss (Alabed, Javornik and Gregory-Smith, 2022).

Verbal-linguistic AI allows personalized feedback and recommendation generation at the post-recovery stage. By analysing customer feedback and recovery interactions, verbal-linguistic AI can generate personalized recommendations for service improvement. This demonstrates a commitment to learning and growth, fostering trust and enhancing future service experiences (Anvar Shathik and Krishna Prasad, 2020; Jain, Pamula and Srivastava, 2021). In addition, it enables automated reporting and knowledge sharing as AI can create comprehensive reports analysing the service failure, recovery process and customer feedback. These reports can be shared internally to improve internal processes and inform future service design, ensuring lessons learned are not lost. Verbal-linguistic AI also enables training and knowledge base development as it can analyse recovery conversations and identify best practices employed by customer service representatives. This information can be utilized to create training materials and knowledge bases, enhancing agent capabilities and ensuring consistent high-quality service in the future (Alabed, Javornik and Gregory-Smith, 2022).

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Logic-mathematical AI enables root cause analysis and recurrence prevention at the post-recovery stage. Continued analysis of the failure event and associated data using logic-mathematical AI can reveal deeper insights into root causes. This knowledge can be used to implement preventative measures and eliminate vulnerabilities within the service system, minimizing the risk of recurrence (Surendran, Khalaf and Tavera Romero, 2022). In addition, logic-mathematical AI models enable predictive maintenance and service optimization as it can be updated with post-recovery data to refine their predictive capabilities. This allows for earlier detection of potential issues and proactive maintenance interventions, preventing future service disruptions and enhancing overall service reliability. Furthermore, this type of AI allows scenario simulation and risk assessment. By simulating various scenarios based on the original service failure and post-recovery data, logic-mathematical AI can identify potential vulnerabilities in existing recovery protocols. This proactive risk assessment allows for continuous improvement and optimization of recovery strategies for future incidents (Habbal, Ali and Abuzaraida, 2024).

Processing-speed AI enables real-time customer satisfaction tracking at the post-recovery stage: analysing customer feedback and interactions in real time post-recovery allows for continuous monitoring of customer satisfaction. Processing-speed AI can identify emerging issues or concerns, prompting further corrective actions and ensuring complete customer satisfaction (Habbal, Ali and Abuzaraida, 2024).

Combining these four AI types in the post-recovery phase creates a multifaceted and powerful approach through continuous learning and improvement and strengthened customer relationships. This holistic approach fosters trust and loyalty within B2B partnerships.

Therefore, we propose the following hypothesis:

H2:There are significant differences between the stages (Stage 1 to Stage 4) of the B2B service recovery journey in terms of the AI intelligence types (logic-mathematical (a), processing-speed (b), social (c), verbal-linguistic (d) and visual-spatial (e)).

Study 2

Study 2 aimed to build on the findings of the exploratory study and Study 1 by examining which AIs (i) are more reflective of human intelligence and (ii) affect performance (from the managerial perspective) at each of the four main stages of the B2B service recovery journey. This allowed us to understand how humans and AI can best collaborate at each stage.

Procedure

We collected data from 525 managers in B2B firms using AI in marketing and customer support. Responses were obtained through the Centiment platform, known for high-quality response data. Web Appendix C details data collection procedures, ensuring validity and generalizability. For detailed insights into human–AI collaboration in B2B service recovery, respondents were questioned on all four B2B service recovery stages. Measurement items for the five AIs were adopted from Pantano and Scarpi (2022). The survey also included 'manager's perceived service recovery performance' using items from Ahmad *et al.* (2022) on a seven-point Likert scale. Web Appendix F lists all measurement items.

We explored the impact of factors identified in our exploratory study, including failure severity, service complexity, firm size and age, client size, industry type and relationship length. Attention checks and time tracking ensured data quality. A pilot study with 25 managers and one researcher preceded primary analysis, reliability and validity assessment. The final sample for analysis comprised 451 completed responses.

Sample characteristics

Respondents were primarily aged 36–45 (51%), male (64%), holding senior managerial positions (79.2%) and possessing a Master's degree (49.2%) (Web Appendix D). All respondents were marketing managers. Firms, mostly located in the United States (65.5%), were 6–10 years old (42.4%). Predominantly firms employed 501–1000 people (57%), operated in finance (34%) and offered finance B2B services (40%). Many firms (37%) had 4–5 years of client relationships, with almost half (45.5%) catering to large clients.

Common service failures included cybersecurity issues (68%), malfunctioning automation platforms (60%), bugs in automated platforms (71%) and delayed service delivery (52%). Participants categorized failures by severity: extremely simple (21%), neutral (14%), severe (10%), somewhat severe (26%) and extremely severe (14%).

Throughout the B2B service recovery journey, commonly used AI systems included chatbots, machine learning, predictive analytics, speech recognition, NLP, predictive analytics (dashboards), recommendation engines, ChatGPT, sentiment analysis and AI-enabled report analysis (Web Appendix E), aligning with Study 1 results. Finally, to examine the proposed theoretical model, we employed structural equation modelling using AMOS software. The two-stage approach (Hair *et al.*, 2019) involved evaluating the measurement model for goodness-of-fit (GoF), reliability and construct validity, followed by testing the hypothesized relationships.

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Results

To evaluate the measurement model, we performed a confirmatory factor analysis. The GoF indices were satisfactory (χ^2/df = 2.315; SRMR = 0.071; RMSEA = 0.039, CFI = 0.901; AGFI = 0.926; TLI = 0.921; NFI = 0.943; see Hair *et al.*, 2019). All constructs met the minimum thresholds for internal consistency (Cronbach's alpha and composite reliability were above 0.7) and convergent validity (outer loadings were above 0.6 and average variance extracted was above 0.5) (Hair *et al.*, 2019) (Web Appendix F). The results passed Fornell and Larcker's (1981) test of discriminant validity because the square root of the AVE coefficients for all constructs was greater than the correlations for all pairs of constructs (Web Appendix G).

Next, we assessed our proposed hypotheses (Figure 1). The variance inflation factor values for all relationships were between 1.000 and 4.912 (Table 4), indicating that there is no collinearity in the study (Hair *et al.*, 2019). In addition, our study shows that the GoF statistics indicate an acceptable fit for the structural model (χ^2/df = 2.596; SRMR = 0.077; RMSEA = 0.045; AGFI = 0.910; TLI = 0.905; NFI = 0.936) and there is no issue with common method variance (Web Appendix H), thus the path coefficients can be confidently estimated (Table 4). Specifically, logic-mathematical intelligence significantly influences MPSRP in Stage 3 ($\beta = 0.187$, p = 0.022) and Stage 4 ($\beta = 0.131$, p = 0.035) only; thus, the evidence partly supports H1. Processing-speed intelligence has a significant influence on MPSRP at every stage (Stage 1: $\beta =$ 0.244; Stage 2: $\beta = 0.190$; Stage 3: $\beta = 0.160$; Stage 4: β = 0.258, $p < 0.05$), fully supporting H2. In turn, social intelligence has a significant influence on MPSRP in Stage 2 ($\beta = 0.306$, p = 0.002), Stage 3 ($\beta = 0.224$, p = 0.016) and Stage 4 ($\beta = 0.220$, p = 0.011), but not Stage 1 ($\beta = 0.022$, p = 0.376), partly supporting H3. Moreover, verbal-linguistic intelligence significantly influences MPSRP in Stage 3 ($\beta = 0.142$, p = 0.041) and Stage 4 ($\beta = 0.160$, p = 0.036) only, meaning that H4 is also partly supported. H5 is partly supported, as visual-spatial intelligence has significant effects on MPSRP in Stage 1 ($\beta = 0.145$, p = 0.039) only. Overall, these results displayed a coefficient of determination (R^2) of 42.4% after we included the insignificant results ($p > 0.05$) of the control variables (age, company position, country, education level, length of relationship, firm age, firm size, gender, industry type, client size, type of B2B services offered, failure severity and failure type). Notably, our results also show that all five AIs are significant ($p < 0.01$) and have stronger estimates when predicting the following stages (or carry-over effect), with β ranging from 0.700 to 0.941 as well as R^2 ranging from 49.0% to 88.6%. Finally, our robustness check confirms the stability of these results (see Web Appendix I for the endogeneity test). Figure 2 presents a summary of our proposed direct relationships.

Finally, we performed an analysis of variance (ANOVA) to ensure that the five types of AIs vary in their significance across the four stages. The result indicates significant differences in each stage for logic-mathematical (p = 0.049), visual-spatial (p = 0.004), social (p = 0.012), verbal-linguistic (p = 0.010) and processing-speed (p = 0.000) intelligence (Web Appendix J). This result supports H2a–e. Web Appendix K shows detailed comparisons of the five AIs at each stage.

Discussion and theoretical implications

This research aimed to develop a theoretical framework of managers' perceptions of the AIs that are essential in each stage of the B2B service recovery journey, thereby facilitating successful collaborations between humans and AI. To achieve this, two studies were conducted. The exploratory study involved senior managers engaged in B2B service recovery in global firms that offer B2B services and use AI in their marketing processes. This study provided insights into the four main stages of the B2B service recovery journey: prediction, detection, recovery and post-recovery. It also revealed the roles played by humans and AI at each stage of the journey.

Building upon Study 1, in Study 2 we empirically tested and validated the theoretical model proposed in this research, which identified the specific AIs required at each stage of the B2B service recovery journey. The study revealed that logic-mathematical, social, verbal-linguistic, visual-spatial and processing-speed intelligence significantly influence B2B service recovery performance (as perceived by managers). Furthermore, the findings indicated that each of the four stages requires AI with different types of intelligence. Specifically, the *prediction* stage benefits from collaborations involving processing speed and visual-spatial AI; the *detection* stage requires logic-mathematical, social and processing-speed AI; the *recovery* stage requires logic-mathematical, social, verbal-linguistic and processing-speed AI; the *post-recovery* stage calls for social, verbal-linguistic, logic-mathematical and processing-speed AI.

This research provides empirical evidence that answers the calls to develop effective ways for humans and AI to collaborate in service contexts, as advocated by recent studies (Ameen *et al.*, 2022; Bond *et al.*, 2020; Huang and Rust, 2022; Pantano and Scarpi, 2022). Furthermore, it contributes to the literature on B2B service recovery management (Baliga *et al.*, 2021; Grégoire and Mattila, 2021; Van Vaerenbergh *et al.*, 2019), which identified that managing service recovery is more challenging in the B2B context because of the complexity and the (financial and non-financial) risks

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

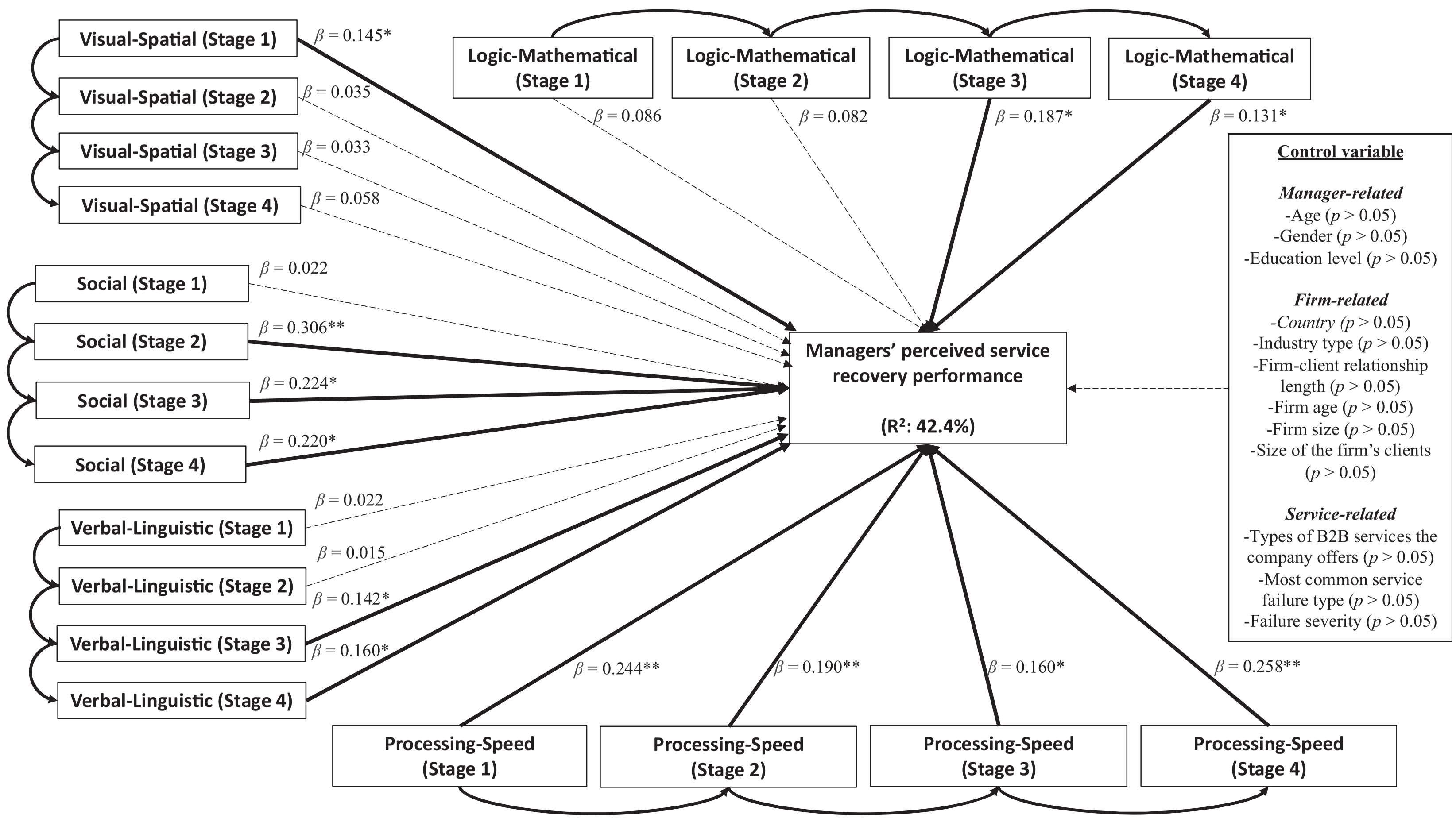

*Figure 2. Overall results of the direct relationships in the proposed model. Note: Solid arrows represent significant results, while dashed arrows represent insignificant results; * means < 0.05; ** means < 0.01.*

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 4. Path estimates

Relationship		Estimate (β)	SE	p-Value	VIF	R^2
Direct effect	LM-Stage 1 → MPSRP	0.086	0.081	0.125	4.118	0.424
	LM-Stage 2 → MPSRP	0.082	0.083	0.131	4.588	
	LM-Stage 3 → MPSRP	0.187	0.081	**0.022**	4.596	
	LM-Stage 4 → MPSRP	0.131	0.074	**0.035**	4.422	
	PS-Stage 1 → MPSRP	0.244	0.093	**0.000**	4.673	
	PS-Stage 2 → MPSRP	0.190	0.103	**0.005**	4.517	
	PS-Stage 3 → MPSRP	0.160	0.092	**0.039**	4.034	
	PS-Stage 4 → MPSRP	0.258	0.075	**0.000**	4.811	
	Soc-Stage 1 → MPSRP	0.022	0.060	0.376	4.115	
	Soc-Stage 2 → MPSRP	0.306	0.098	**0.002**	4.713	
	Soc-Stage 3 → MPSRP	0.224	0.091	**0.016**	4.289	
	Soc-Stage 4 → MPSRP	0.220	0.079	**0.011**	4.897	
	VL-Stage 1 → MPSRP	0.022	0.095	0.390	4.598	
	VL-Stage 2 → MPSRP	0.015	0.098	0.445	4.288	
	VL-Stage 3 → MPSRP	0.142	0.082	**0.041**	4.061	
	VL-Stage 4 → MPSRP	0.160	0.075	**0.036**	4.912	
	VS-Stage 1 → MPSRP	0.145	0.085	**0.039**	4.524	
	VS-Stage 2 → MPSRP	0.035	0.086	0.331	4.053	
	VS-Stage 3 → MPSRP	0.033	0.085	0.366	4.836	
	VS-Stage 4 → MPSRP	0.058	0.080	0.227	4.879	
Control variable	Age → MPSRP	−0.008	0.049	0.420	1.919	
	Company position → MPSRP	0.004	0.069	0.458	1.433	
	Country → MPSRP	0.048	0.083	0.108	1.590	
	Education level → MPSRP	0.021	0.049	0.298	1.906	
	Length of relationship → MPSRP	0.025	0.045	0.258	1.997	
	Firm age → MPSRP	0.062	0.040	0.057	1.685	
	Firm size → MPSRP	0.011	0.047	0.393	1.834	
	Gender → MPSRP	−0.028	0.082	0.238	1.967	
	Industry type → MPSRP	−0.035	0.020	0.186	1.620	
	Client size → MPSRP	−0.008	0.049	0.422	1.584	
	Types of B2B service offered → MPSRP	0.056	0.037	0.075	1.780	
	Failure severity → MPSRP	0.041	0.018	0.569	1.952	
	Failure type → MPSRP	0.044	0.031	0.289	1.679	
Carry-over effect	LM-Stage 1 → LM-Stage 2	0.766	0.058	**0.000**	1.000	0.587
	LM-Stage 2 → LM-Stage 3	0.884	0.078	**0.000**	1.000	0.781
	LM-Stage 3 → LM-Stage 4	0.941	0.069	**0.000**	1.000	0.886
	PS-Stage 1 → PS-Stage 2	0.700	0.031	**0.000**	1.000	0.490
	PS-Stage 2 → PS-Stage 3	0.789	0.036	**0.000**	1.000	0.623
	PS-Stage 3 → PS-Stage 4	0.844	0.028	**0.000**	1.000	0.712
	Soc-Stage 1 → Soc-Stage 2	0.825	0.025	**0.000**	1.000	0.681
	Soc-Stage 2 → Soc-Stage 3	0.891	0.023	**0.000**	1.000	0.794
	Soc-Stage 3 → Soc-Stage 4	0.913	0.021	**0.000**	1.000	0.834
	VL-Stage 1 → VL-Stage 2	0.732	0.030	**0.000**	1.000	0.536
	VL-Stage 2 → VL-Stage 3	0.805	0.032	**0.000**	1.000	0.648
	VL-Stage 3 → VL-Stage 4	0.868	0.027	**0.000**	1.000	0.753
	VS-Stage 1 → VS-Stage 2	0.797	0.051	**0.000**	1.000	0.635
	VS-Stage 2 → VS-Stage 3	0.891	0.069	**0.000**	1.000	0.794
	VS-Stage 3 → VS-Stage 4	0.930	0.070	**0.000**	1.000	0.865

Note: VIF: variance inflation factor. Values in **bold** are significant. LM: logic-mathematical; PS: processing-speed; Soc: social; VL: verbal-linguistic; VS: visual-spatial; MPSRP: managers' perceived service recovery performance.

involved (Baliga *et al.*, 2021; Grégoire and Mattila, 2021; Zhu and Zolkiewski, 2015). To the best of our knowledge, ours is the first research to unpack the B2B service recovery journey and investigate the specific AIs required at each stage for successful human–AI collaboration.

Two significant contributions arise from this research. Firstly, it provides empirical evidence that extends the theory of intelligences (Huang and Rust, 2018; Pantano and Scarpi, 2022) to the B2B context by revealing the specific AIs required at each stage of the B2B service recovery journey. Secondly, this research builds upon work by Van Vaerenbergh *et al.* (2019). Our research expands on the studies of Van Vaerenbergh *et al.* (2019) and Grégoire and Mattila (2021) by identifying four distinct stages of B2B service recovery based on

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

human–AI collaboration: prediction, detection, during recovery and post-recovery.

Regarding the technical aspects of AI in organizations, the successful implementation of AI in B2B service recovery relies on machine learning, NLP and data analytics, tailored to each stage of the service recovery journey. In the prediction stage, machine learning and predictive analytics identify patterns and anticipate potential failures. During detection, NLP, speech recognition, machine learning and chatbots detect issues from customer interactions. In the recovery stage, recommendation engines, chatbots, predictive analytics systems, NLP, sentiment analysis systems and ChatGPT provide personalized solutions. Post-recovery, predictive analytics, report analysis and chatbots enable continuous improvement. Implementing these technologies requires robust data management and integration. Emerging approaches like transfer learning and explainable AI can further enhance AI-driven service recovery across all stages. However, organizations must navigate technical challenges, such as the automation–augmentation paradox (Raisch and Krakowski, 2021), while ensuring seamless integration with existing systems. As AI advances, organizations must stay abreast of developments and adopt an iterative approach to harness its full potential in service recovery.

Managerial implications

This research offers several implications for managers. Human–AI collaborations in the B2B service recovery process emerged as crucial for enhancing performance, especially in firms that strive to provide smart services while meeting the growing demand for quicker recovery and minimal service failures. By recognizing service recovery as a journey with four main stages – prediction, detection, recovery and post-recovery – managers and practitioners can proactively address the specific requirements and objectives of each stage.

Our research highlights that not all AIs hold equal importance across all stages of the B2B service recovery journey. Consequently, managers should carefully integrate the appropriate type into each stage to optimize collaboration between AI and practitioners. For instance, including logic-mathematical AI intelligence during the detection and recovery stages can enhance the effectiveness of the recovery process. Similarly, integrating social AI intelligence into the detection, recovery and post-recovery stages can foster better interactions and support for clients.

This research offers practical guidance for managers aiming to improve B2B service recovery using AI–human collaboration. By recognizing the needs of each stage and integrating the appropriate types of AI, organizations can enhance their service recovery capabilities, ultimately providing enhanced customer experiences.

Limitations and future research

To address the limitations of this research and guide future investigations, several areas for further studies can be identified. While our study primarily focused on the perspective of service providers, future research can delve into the client's viewpoint, specifically examining the role of different types of AI in achieving client satisfaction during the B2B service recovery process. Furthermore, our results are based on data collected from managers in China. Future studies can collect data from other developed and developing countries, and compare the findings with the findings of this study.

In addition, our study measured managers' perceptions of overall B2B service recovery performance as the dependent variable. To gain a better understanding, future studies should collect data to assess the impact of various AIs on managers' perceptions of performance in each of the four stages – prediction, detection, recovery and post-recovery – as well as overall performance. This granular analysis would not only contribute to a better comprehension of the intricate interplay between AI and human evolution, but also offer valuable insights for managers to refine strategies and interventions across the entire service recovery spectrum. By delving into these aspects, future research can provide a richer theoretical debate on the evolving role of different intelligences in B2B service recovery, fostering a deeper understanding of how the synergy between machines and humans shapes the landscape and influences managerial perspectives. Finally, future studies can explore managers' perceptions of regenerative AI and quantum computing and the potential of these technologies in improving B2B service recovery, as well as the management-related challenges in this context.

Acknowledgements

We extend our heartfelt thanks to the experts whose insights contributed significantly to this study, with special gratitude to the late Renaud Champion for their precious contributions.

References

Agnihotri, A. and S. Bhattacharya (2024). 'Chatbots' effectiveness in service recovery', *International Journal of Information Management*, **76**, art. 102679.

Ahmad, B., D. Liu, N. Akhtar and U. I. Siddiqi (2022). 'Does service–sales ambidexterity matter in business-to-business service recovery? A perspective through salesforce control system', *Industrial Marketing Management*, **102**, pp. 351–363.

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Alabed, A., A. Javornik and D. Gregory-Smith (2022). 'AI anthropomorphism and its effect on users' self-congruence and self–AI integration: a theoretical framework and research agenda', *Technological Forecasting and Social Change*, **182**, art. 121786.

Ameen, N., G. D. Sharma and S. Y. Tarba (2024). 'Artificial intelligence and creativity in marketing: a proposed typology and new directions for academia–industry collaborations'. In M. Pagani and R. Champion (eds), *Artificial Intelligence for Business Creativity*, pp. 82–98. London: Routledge.

Ameen, N., G. D. Sharma, S. Y. Tarba, A. Rao and R. Chopra (2022). 'Toward advancing theory on creativity in marketing and artificial intelligence', *Psychology & Marketing*, **39**, pp. 1802–1825.

Ameen, N., G. Viglia and L. Altinay (2023). 'Revolutionizing services with cutting-edge technologies post major exogenous shocks', *The Service Industries Journal*, **43**, pp. 125–133.

Anvar Shathik, J. and K. Krishna Prasad (2020). 'A literature review on application of sentiment analysis using machine learning techniques', *International Journal of Applied Engineering and Management Letters*, **4**, pp. 41–77.

Ashok, M., M. Day and R. Narula (2018). 'Buyer (dis)satisfaction and process innovation: the case of information technology services provision', *Industrial Marketing Management*, **68**, pp. 132–144.

Balakrishnan, J. and Y. K. Dwivedi (2021). 'Role of cognitive absorption in building user trust and experience', *Psychology & Marketing*, **38**, pp. 643–668.

Baliga, A. J., V. Chawla, L. S. Ganesh and B. Sivakumaran (2021). 'Service failure and recovery in B2B markets – a morphological analysis', *Journal of Business Research*, **131**, pp. 763–781.

Belk, R., E. Fischer and R. V. Kozinets (2013). *Qualitative Consumer and Marketing Research*. London: Sage.

Bond III, E. U., A. de Jong, A. Eggert, M. B. Houston, M. Kleinaltenkamp, A. K. Kohli, *et al.* (2020). 'The future of B2B customer solutions in a post-COVID-19 economy: managerial issues and an agenda for academic inquiry', *Journal of Service Research*, **23**, pp. 401–408.

Brock, C., M. Blut, H. Evanschitzky and P. Kenning (2013). 'Satisfaction with complaint handling: a replication study on its determinants in a business-to-business context', *International Journal of Research in Marketing*, **30**, pp. 319–322.

Brown, O., R. Davidson, S. Decker, D. Ellis, J. Faulconbridge, J. Gore, *et al.* (2024). 'Theory-driven perspectives on generative artificial intelligence in business and management', *British Journal of Management*, **35**, pp. 3–23.

Chang, W. (2022). 'The effectiveness of AI salesperson vs. human salesperson across the buyer–seller relationship stages', *Journal of Business Research*, **148**, pp. 241–251.

Chaturvedi, R., S. Verma, R. Das and Y. K. Dwivedi (2023). 'Social companionship with artificial intelligence: recent trends and future avenues', *Technological Forecasting and Social Change*, **193**, art. 122634.

Chugh, R., N. G. Mark, P. Leach and A. H. Liu (2023). 'B2B buyers' emotions and regulatory focus in justice and switch back decisions', *Industrial Marketing Management*, **109**, pp. 73–89.

Doney, P. M., J. M. Barry and R. Abratt (2007). 'Trust determinants and outcomes in global B2B services', *European Journal of Marketing*, **41**, pp. 1096–1116.

Esmaeilzadeh, H. and R. Vaezi (2022). 'Conscious empathic AI in service', *Journal of Service Research*, **25**, pp. 549–564.

Fornell, C. and D. F. Larcker (1981). 'Evaluating structural equation models with unobservable variables and measurement error', *Journal of Marketing Research*, **18**, pp. 39–50.

Fotheringham, D. and M. A. Wiles (2023). 'The effect of implementing chatbot customer service on stock returns: an event study analysis', *Journal of the Academy of Marketing Science*, **51**, pp. 802–822.

Gardner, H. (1983). *Frames of Mind: The Theory of Multiple Intelligences*. New York: Basic Books.

Grégoire, Y. and A. S. Mattila (2021). 'Service failure and recovery at the crossroads: recommendations to revitalize the field and its influence', *Journal of Service Research*, **24**, pp. 323–328.

Gupta, S., Y. Wang and M. Czinkota (2023). 'Reshoring: a road to Industry 4.0 transformation', *British Journal of Management*, **34**, pp. 1081–1099.

Guzman, A. L. and S. C. Lewis (2019). 'Artificial intelligence and communication: a human–machine communication research agenda', *New Media and Society*, **22**, pp. 70–86.

Habbal, A., M. K. Ali and M. A. Abuzaraida (2024). 'Artificial Intelligence Trust, Risk and Security Management (AI TRiSM): frameworks, applications, challenges and future research directions', *Expert Systems with Applications*, **240**, art. 122442.

Habel, J., S. Alavi and N. Heinitz (2023). 'Effective implementation of predictive sales analytics', *Journal of Marketing Research*, DOI: https://doi.org/10.1177/00222437221151039.

Hair, J. F., W. C. Black, B. J. Babin and R. E. Anderson (2019). *Multivariate Data Analysis*, 8th edn. London: Cengage Learning.

Hajli, N., U. Saeed, M. Tajvidi and F. Shirazi (2022). 'Social bots and the spread of disinformation in social media: the challenges of artificial intelligence', *British Journal of Management*, **33**, pp. 1238–1253.

Hess Jr, R. L., S. Ganesan and N. M. Klein (2003). 'Service failure and recovery: the impact of relationship factors on customer satisfaction', *Journal of the Academy of Marketing Science*, **31**, pp. 127–145.

Huang, M. and R. T. Rust (2018). 'Artificial intelligence in service', *Journal of Service Research*, **21**, pp. 155–172.

Huang, M. and R. T. Rust (2021). 'A strategic framework for artificial intelligence in marketing', *Journal of the Academy of Marketing Science*, **49**, pp. 30–50.

Huang, M. and R. T. Rust (2022). 'A framework for collaborative artificial intelligence in marketing', *Journal of Retailing*, **98**, pp. 209–223.

Jain, P. K., R. Pamula and G. Srivastava (2021). 'A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews', *Computer Science Review*, **41**, art. 100413.

Khamitov, M., Y. Grégoire and A. Suri (2020). 'A systematic review of brand transgression, service failure recovery and product-harm crisis: integration and guiding insights', *Journal of the Academy of Marketing Science*, **48**, pp. 519–42.

Koc, E. (2017). *Service Failures and Recovery in Tourism and Hospitality: A Practical Manual*. Oxford: CABI Publishing.

Kranzbühler, A. M., A. Zerres, M. H. Kleijnen and P. W. Verlegh (2020). 'Beyond valence: a meta-analysis of discrete emotions in firm–customer encounters', *Journal of the Academy of Marketing Science*, **48**, pp. 478–498.

Liu-Thompkins, Y., S. Okazaki and H. Li (2022). 'Artificial empathy in marketing interactions: bridging the human–AI gap in affective and social customer experience', *Journal of the Academy of Marketing Science*, **50**, pp. 1198–1218.

Luo, X., M. S. Qin, Z. Fang and Z. Qu (2021). 'Artificial intelligence coaches for sales agents: caveats and solutions', *Journal of Marketing*, **85**, pp. 14–32.

Lv, X., Y. Yang, D. Qin, X. Cao and H. Xu (2022). 'Artificial intelligence service recovery: the role of empathic response in hospitality customers' continuous usage intention', *Computers in Human Behavior*, **126**, art. 106993.

Naumann, E., M. Haverila, M. S. Khan and P. Williams (2010). 'Understanding the causes of defection among satisfied B2B service customers', *Journal of Marketing Management*, **26**, pp. 878–900.

Nguyen, T. and A. Malik (2022). 'A two-wave cross-lagged study on AI service quality: the moderating effects of the job level and job role', *British Journal of Management*, **33**, pp. 1221–1237.

Pagani, M. and R. Champion (2020, November 17). 'Making sense of the AI landscape', Harvard Business Review. https://hbr.org/2020/11/making-sense-of-the-ai-landscape.

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Pantano, E. and D. Scarpi (2022). 'I, robot, you, consumer: measuring artificial intelligence types and their effect on consumers' emotions in service', *Journal of Service Research*, **25**, pp. 583–600.

Pizzi, G., D. Scarpi and E. Pantano (2021). 'Artificial intelligence and the new forms of interaction: who has the control when interacting with a chatbot?', *Journal of Business Research*, **129**, pp. 878–890.

Puntoni, S., R. W. Reczek, M. Giesler and S. Botti (2021). 'Consumers and artificial intelligence: an experiential perspective', *Journal of Marketing*, **85**, pp. 131–151.

Raisch, S. and S. Krakowski (2021). 'Artificial intelligence and management: the automation–augmentation paradox', *Academy of Management Review*, **46**, pp. 192–210.

Russell, S. J. and P. Norvig (2009). *Artificial Intelligence: A Modern Approach*. Englewood Cliffs, NJ: Prentice Hall.

Rust, R. T. and M. Huang (2021). *The Feeling Economy: How Artificial Intelligence is Creating the Era of Empathy*. Cham: Palgrave Macmillan.

Sands, S, C. Campbell, C. Ferraro and K. Plangger (2022). 'Buffering B2B service failure: the role of customer engagement', *Industrial Marketing Management*, **103**, pp. 47–60.

Sarker, I. H. (2021). 'Machine learning: algorithms, real world applications and research directions', *SN Computer Science*, **2**, pp. 1–21.

Schneider, W. J. and K. S. McGrew (2012). 'The Cattell–Horn–Carroll model of intelligence'. In D. P. Flanagan and P. L. Harrison (eds), *Contemporary Intellectual Assessment: Theories, Tests, and Issues*, pp. 99–144. New York: Guilford Press.

Shin, H., A. E. Ellinger, D. L. Mothersbaugh and K. E. Reynolds (2017). 'Employing proactive interaction for service failure prevention to improve customer service experiences', *Journal of Service Theory and Practice*, **27**, pp. 164–186.

Solomon, M. and Y. H. Lo (2022). 'Visual-spatial processing: the parietal lobe in engaging a 3D world'. In M. Albert, L. Lin, M. Spector and L. Dunn (eds), *Bridging Human Intelligence and Artificial Intelligence*, pp. 207–221. Cham: Springer International.

Strauss, A. and J. Corbin (1998). *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*, 2nd edn. Thousand Oaks, CA: Sage.

Suhaili, S. M., N. Salim and M. N. Jambli (2021). 'Service chatbots: a systematic review', *Expert Systems with Applications*, **184**, art. 115461.

Surendran, R., O. I. Khalaf and C. A. Tavera Romero (2022). 'Deep learning based intelligent industrial fault diagnosis model', *Computers, Materials & Continua*, **70**, pp. 6323–6338.

Van Vaerenbergh, Y., D. Varga, A. D. Keyser and C. Orsingher (2019). 'The service recovery journey: conceptualization, integration, and directions for future research', *Journal of Service Research*, **22**, pp. 103–119.

Webster, J., L. K. Trevino and L. Ryan (1993). 'The dimensionality and correlates of flow in human–computer interactions', *Computers in Human Behavior*, **9**, pp. 411–426.

Zhu, X. and J. Zolkiewski (2015). 'Exploring service failure in a business-to-business context', *Journal of Services Marketing*, **29**, pp. 367–379.

Nisreen Ameen is a Senior Lecturer (Associate Professor) in Digital Marketing at Royal Holloway, University of London and Co-Director of the Digital Organisation and Society research centre. Nisreen is also currently serving as Vice President of the UK Academy of Information Systems (UKAIS). Nisreen's research focuses on two main themes: first, consumer interactions with cutting-edge technologies; and second, how organizations can use these technologies to provide better experiences, services and products.

Margherita Pagani is a Full Professor PhD HDR of Digital and Artificial Intelligence in Marketing and Director of the SKEMA Centre for Artificial Intelligence at SKEMA Business School in Paris. She also holds the position of Research Affiliate at the Berkeley APEC Study Center (BASC) at the University of California, Berkeley. Additionally, she serves as an Advisor for the European Economic and Social Committee (EESC), focusing on the European metaverse and virtual worlds.

Eleonora Pantano is an Associate Professor (Reader) of Retail and Marketing Technology. Her research activities mainly relate to the development of new customer solutions and retail management strategies, with emphasis on the role of new technology, artificial intelligence and machine learning algorithms.

Jun-Hwa Cheah (Jacky) is an Associate Professor at Norwich Business School, University of East Anglia. His areas of interest include consumer behaviour, quantitative research and methodological issues.

Shlomo Y. Tarba is Chair (Full Professor) of Strategy & International Business, University of Birmingham. He is a Fellow of Academy of Social Sciences. His research interests include M&A, agility and AI. His papers are published in the *Journal of Management*, *Journal of Product Innovation Management*, *Journal of Organizational Behaviour, Human Relations, Academy of Management Perspectives,* and *Journal of Service Research*.

Senmao Xia is a Senior Lecturer (Associate Professor) in Digital Economy, Entrepreneurship and Innovation & the Programme Director of Blockchain Business Models at the University of Surrey, UK. He has published papers at the *British Journal of Management, Technovation, Journal of Business Research*, and so forth. Senmao serves as the Vice President for Chinese Economic Association (Europe/UK) and acts as the editorial leadership for multiple international journals, including, the *Journal of Chinese Economic and Business Studies, the Journal of Innovation and Knowledge*, and so forth. Senmao is the Senior Fellow of Higher Education Academy, UK (SFHEA). He acts as an advisor for a few firms in London.

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Supporting Information

Additional supporting information can be found online in the Supporting Information section at the end of the article.

© 2024 The Authors. *British Journal of Management* published by John Wiley & Sons Ltd on behalf of British Academy of Management.

14678551, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1467-8551.12829 by University Of East Anglia, Wiley Online Library on [13/08/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License