Artificial intelligence in service industries: customers' assessment of service production and resilient service operations

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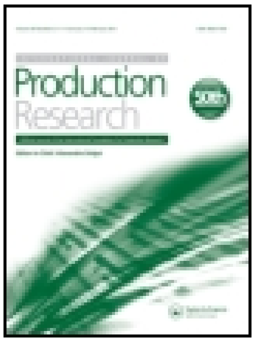

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Artificial intelligence in service industries: customers' assessment of service production and resilient service operations

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ABSTRACT
Artificial intelligence (AI) is increasingly embedded into service firms' operations. However, production systems and operations management scholars have not yet examined if AI-empowered service operations are positively judged by service customers. To bridge this gap, this study draws on the three-factor theory of customer satisfaction applied to online review data, to capture the effect of AI-empowered service operations on overall customer satisfaction, operationalised by means of online review ratings. Based on text analytics techniques applied to a sample of more than 50,000 TripAdvisor ORs covering 35 international hotels in Asia and America, we develop a penalty–reward contrast analysis. The findings reveal that the effects of customer interaction with mechanical AI on customer satisfaction with service operations are asymmetric: positive customer interaction with mechanical AI positively and significantly influences overall customer satisfaction with AI-empowered service operations, whereas negative customer interaction with mechanical AI does not significantly alter customer satisfaction. Taken together, these findings suggest that mechanical AI constitutes a key element of resilient AI-empowered service operations.

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Artificial intelligence; service operations; resilience; service robots; customer satisfaction; online reviews

1. Introduction

An increasing range of digital technologies is propelling the digital transformation of business and driving the fourth industrial revolution (Müller, Buliga, and Voigt 2018) across numerous industries, including both manufacturing and service industries (D'Ambra, Akter, and Mariani 2022; Mariani and Borghi 2019). Therefore, digital technology developments are profoundly influencing both production systems and operations management. Among digital technologies, artificial intelligence (AI) is playing a critical role not only in transforming business, production systems and operations management (Dwivedi et al. 2019; Gartner 2019), but also in business process management (Queiroz et al. 2020).

In service industries, AI has been recognised as a major driver for the digital transformation of service operations (Huang and Rust 2018, 2021; Jörling, Böhm, and Paluch 2019; Wang, Skeete, and Owusu 2021). Indeed, AI – especially mechanical AI-like robots – allows service firms to increasingly automate their business and production processes, as well as operations, in search of enhanced efficiency. However, compared to manufacturing industries, service industries are distinctively different in that the final outcome of a production process, namely the service, is co-created by the service producer and the service customer (Grönroos and Voima 2013). Therefore, when analysing the role of AI in operations within service industries, it is of paramount importance to take into account customers' perceptions of AI-empowered service operations. Indeed, within the service realm, AI is capable of modifying customers' role in service co-creation (Larivière et al. 2017), which ultimately has an impact on AI-empowered service operations.

So far, production systems and operations management scholars have mainly focused on applications of AI in the manufacturing industry (Pillai et al. 2022), thus empirically overlooking the impact of AI on service operations. This stems from an advanced search of Scopus that we conducted, following the guidelines for effective systematic literature reviews (Paul et al. 2021). More specifically, we conducted an advanced search in Scopus with three conjoint queries: (1) the first searching the terms 'AI' OR 'artificial intelligence', in the title, abstract and keywords; (2) the second searching the terms 'services firms' OR 'service industry' OR 'service industries' OR hospitality OR 'service sector', in the title, abstract and keywords; (3) the third searching the term 'customer satisfaction' in the title, abstract and keywords.

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This article has been corrected with minor changes. These changes do not impact the academic content of the article.

The three queries were later combined using the Boolean operator 'AND'. The query returned 28 documents. Of these, 17 are mere conference proceedings covering very marginal methodological aspects and were excluded. Of the remaining 11 articles, we retained both articles published in an ABS journal with an ABS rating > 2, and articles with an Impact Factor in 2022 superior to 2. This led to the identification of seven scientific articles (e.g. González-Rodríguez, Díaz-Fernández, and Gómez 2020; Li et al. 2021; Oh et al. 2022; Pyon, Woo, and Park 2011) that do not deal specifically with the examination of the effect of AI-empowered service operations on customers from a production systems and operations management perspective. This is rather surprising as professional service robots are increasingly adopted by organisations and the international market for professional service robots grew in 2020 by 12% from a sample turnover of USD 6.0 billion to USD 6.7 billion (International Federation of Robotics 2021). Additionally, the global pandemic has brought about new opportunities for several service robot applications, as the pandemic created increased awareness of keeping a minimum distance between service staff members and service customers to avoid contact. More specifically, demand for professional cleaning robots has grown by 92% in terms of units sold and by 51% in terms of turnover, and similar figures were recorded for the units sold of medical robotics and hospitality robots. While demand for service robots increases, prices are predicted to decrease over time (Financial Times 2020).

Instead, if we look at service management scholars, they have paid closer attention to the way mechanical AI in the form of service robots is increasingly adopted by service firms (Huang and Rust 2018, 2021). For instance, over the last 15 years, service robots have been increasingly embedded in the operations of service firms, implementing ambidextrous strategies of simultaneous cost compression and service quality improvement (Wirtz and Zeithaml 2018) to be translated into dual value: service operations efficiency and effectiveness. While the integration of service robots in service firms' operations has been the object of several recent conceptual studies (Ruel and Njoku 2020; Tussyadiah, Zach, and Wang 2020), a few descriptive narrations (Ivanov et al. 2019), and an undertheorised study using mere correlations to understand sentiment measures versus service ratings (Luo et al. 2021), not much is known about the extent to which positive or negative customer interaction with mechanical AI influences overall customer satisfaction with AI-empowered service operations.

It is no surprise that service management scholars have recently called for more empirical substantiation of AI in services (Huang and Rust 2018; Rafaeli et al. 2017). In line with studies that have emphasised that for AI-empowered service production it is critical to focus on the 'customer voice' after human–robot interactions (Borghi and Mariani 2022; Lu et al. 2020; Mariani and Borghi 2021), this study bridges an important research gap as it sheds light on the influence of customers' interaction with AI on overall customer satisfaction with AI-empowered services.

Automation is supposed to bring productivity gains (Downing and Safizadeh 1997; Säfsten, Winroth, and Stahre 2007), but does not always imply higher customer satisfaction levels (Rust and Huang 2012), and extant production systems and operations management literature have, so far, taken a service provider perspective (Wang, Skeete, and Owusu 2021), but not a more holistic perspective considering also the customer. If service robots are found to play a positive and significant role in terms of both productivity and customer satisfaction, it might be argued that they constitute an effective pathway to achieving differentiation strategies at a lower unit cost. However, this currently represents a research gap in the production systems and operations management literature that has almost exclusively focused on efficiency, productivity, and performance from an organisational perspective rather than from a customer perspective. To fill this critical research gap, we address the following overarching research question: *Does customer interaction with mechanical artificial intelligence influence overall customer satisfaction with AI-empowered service operations?*

Addressing this question is critical as it can contribute to production systems and operations management literature, by determining if the widely acknowledged trade-off between productivity and customer satisfaction still exists in service industries after the introduction of AI into service operations (Rust and Huang 2012; Wirtz and Zeithaml 2018).

To address our research question, we build conceptually on the three-factor theory of customer satisfaction (Matzler and Sauerwein 2002) to analyse the AI-empowered operations of hospitality firms that have been increasingly introducing service robots over the last 15 years. In line with the latest production systems and operations management studies (e.g. Joung and Kim 2021) and other research using user generated content data (Oh et al. 2022), we use online review data. These data are related to a sample of 35 international hotels that introduced AI-empowered delivery services in their operations. AI is indeed redefining the hospitality industry (Ruel and Njoku 2020) at large, and hotel operations. By building on a penalty–reward analytical approach, we deploy text analytics measures to examine the relationship between customer interaction with mechanical AI and overall customer satisfaction with AI-empowered service operations. Consistently, this work aims to extend scholarly knowledge at the intersection of AI in service operations, service operations management, service production, evaluation of customer satisfaction with services, human–robot interaction and online review text analytics.

The manuscript is structured as follows. Section 2 provides an overview of the literature revolving around: AI and service industries; AI in the production of services and resilient service operations; and customer satisfaction with service operations. This way we develop the main research proposition and hypotheses the study aims to test. A description of the methodology and data deployed is presented in Section 3, whereas Section 4 reports the main findings of the study and the robustness checks performed. In Section 5 we discuss the findings, as well as theoretical contributions, practical implications and limitations. Finally, Section 6 presents the conclusion of the study.

2. Literature review

2.1. Artificial intelligence in service industries

There seems to be broad consensus that early writings on artificial intelligence (AI) emerged in science fiction in the 1940s (Minsky 1961a, 1961b; Shubik 1960). In 1942 American science fiction writer Isaac Asimov published his book *Runaround*, in which a robot is developed by engineers Gregory Powell and Mike Donavan, paying attention to the so called 'three rules' of robotics. In a relatively short time, Asimov's book rose to prominence, especially in the circles of computer and robotic scientists. At roughly the same time, the English mathematician Alan Turing worked for the British government on a supercomputer (the Bombe) to break the Enigma code used by the German army during WWII (Haenlein and Kaplan 2019). This experience was conducive in the fifties to the production of an article describing how to create intelligent machines and test their intelligence. Apparently, the periphrasis 'artificial intelligence' was coined in 1956 on the occasion of the Dartmouth Summer Research Project on Artificial Intelligence (DSRAI) hosted at Dartmouth College (U.S.A.) by scientists Marvin Minsky and John McCarthy. Since then, AI and its relevance have recorded many ups and downs, and currently AI technologies play an important role in the Industry 4.0 revolution (Ivanov et al. 2021; Mariani and Borghi 2019; Müller, Buliga, and Voigt 2018). Over time, a number of scholars in business and management have recognised that AI has multiple ramifications. For instance, Davenport and Ronanki (2018) distinguish three types of AI: process automation, cognitive insight and cognitive engagement. In the service domain, Huang and Rust (2018) illustrate and describe four types of AI: mechanical, analytical, intuitive and empathetic. More specifically, *mechanical intelligence* pertains to the ability to perform automatically repeated, routine tasks; *analytical intelligence* relates to the ability to process information aimed at problem-solving and learning; *intuitive intelligence* concerns the ability to think in a creative way and adjust to novel situations; and *empathetic intelligence* is linked to the ability to identify and comprehend human emotions, interact suitably emotionally and impact others' emotions.

Service research scholars have emphasised that service robots are a form of mechanical AI and are typically deployed by service firms to help service employees and customers co-produce the service (Huang and Rust 2018). Indeed, service literature has recognised that service production is about service employee–customer co-production (e.g. Vargo and Lusch 2004). More specifically, mechanical AI has been found to take over standardised and repetitive service tasks, giving service firms the advantage of cost efficiency and quality consistency (Huang and Rust 2018). While AI can easily replace unskilled service labour, more rarely does it replace skilled labour that typically requires creative and abstract thinking and problem-solving capabilities (Autor and Dorn 2013). However, the deployment of AI in services will probably be a threat to human employment (Huang and Rust 2018) and not necessarily brings to a good AI society (Fosso Wamba et al. 2020). More recently, service scholars have underlined that AI plays a positive and significant role in terms of both productivity and customer satisfaction for service firms, and therefore it could be argued that service robots and AI-empowered service devices constitute an effective pathway to achieve differentiation strategies at a lower unit cost or a form of *cost-effective service excellence* (Wirtz and Zeithaml 2018).

2.2. Artificial intelligence in the pro-sumption of services and resilient service operations

Service production in service industries is unique as the final outcome of a production process, namely the service, is co-created by the service producer and the service customer (Grönroos and Voima 2013; Vargo and Lusch 2004). Therefore, when analysing the role of AI in operations within service industries, it is of paramount importance to take into account customers' perceptions of AI-empowered service operations. This aspect is not as central or critical when considering manufacturing industries (Fosso Wamba et al. 2021; Pillai et al. 2022) and, in the sporadic cases when service industries have been analysed in relation to AI (Wang, Skeete, and

Owusu 2021), the customer perspective has been largely neglected. Within the service realm, AI is capable of modifying customers' role in service co-creation (Larivière et al. 2017), which ultimately has an impact on AI-empowered service operations. In other words, the production process in service industries can be related to the phenomenon of 'pro-sumption', which implies that service consumers (and customers) are also producers of the service. This, therefore, implies that when analysing the role of AI in services production, the focus should shift from a 'producer/manufacturer' focus – typical of most of the production systems and operations management literature (Chiarini and Kumar 2021) – to a 'producer and consumer' focus, whereby customers' perceptions of AI-empowered service operations need to be given priority.

Accordingly, in the last lustre, a tiny research stream has emerged in relation to the examination of service customers' perceptions of AI service operations in general, and service robots in particular. More specifically, service research scholars have examined how customer demographics (Yu 2018) and service robots' features (Rodriguez-Lizundia et al. 2015) might influence service customers' perceptions. However, empirical studies examining the impact of AI service operations on customers are limited in number and depth, urging scholars to call for more empirical substantiation of AI-empowered service operations (Huang and Rust 2018; Rafaeli et al. 2017; Wang, Skeete, and Owusu 2021). In line with studies that have emphasised that for AI-empowered service production it is critical to focus on the 'customer voice' after human–robot interactions (Lu et al. 2020; Mariani and Borghi 2021), this study sheds light on the influence of customers' interaction with AI on overall customer satisfaction with AI-empowered services. Therefore, in this study we examine if customer interaction with mechanical artificial intelligence influences overall customer satisfaction with AI-empowered service operations.

This is particularly relevant when unexpected and detrimental events such as natural disasters, pandemics, wars and terrorist attacks force firms to modify their production activities (Nguyen et al. 2022). While this is well documented in the manufacturing sector (Dubey et al. 2021b; Nguyen et al. 2022) it is much less examined in the services sector, where service firms have to modify their production and pro-sumption activities.

Organisational resilience is not easy to achieve during and after such events for organisations in general (Burnard and Bhamra 2011) as they have to streamline their supply chains (Bechtsis et al. 2022; Belhadi et al. 2022; Dubey et al. 2021a). This is even more difficult to achieve for service firms (Jaaron and Backhouse 2014) due to the dual nature of the production process in the service industries. For instance, the COVID-19 pandemic has brought about new opportunities for service robot applications – especially in healthcare services and hospitality services – as there has been increased awareness of keeping a minimum distance between service staff members and service customers to avoid contact (Qubein 2020). We argue that AI-empowered service operations can be more resilient than service operations where AI is not involved, as this allows service firms to be more agile and respond more flexibly to demand fluctuations, as has been observed in the manufacturing sector (Nguyen et al. 2022) and retail (Huber and Stuckenschmidt 2021). The increasing integration of AI devices into service operations has been found to be necessary to allow service firms to improve their agility, flexibility and adaptability (Ivanov and Dolgui 2020) in extreme circumstances. In line with the latest production systems and operations management studies (e.g. Joung and Kim 2021), we use online review data. More specifically, and in line with operational research emphasising the importance of data analytics (Fosso Wamba et al. 2018), we deploy online review analytics to understand if AI-empowered service operations related text in online reviews influences the online review ratings of 35 leading American and Asian hotels that have integrated mechanical AI into their operations.

2.3. Customer satisfaction with service operations

Customer satisfaction represents a complex construct in academic literature whose nature has evolved over time (Anderson, Fornell, and Mazvancheryl 2004). In the mainstream marketing literature, according to the expectation-disconfirmation theory (Oliver 1980), satisfaction is a unidimensional concept which arises as a cognitive comparison between expectations and actual product/service performance. Thus, satisfaction is defined on a single continuum, having at its extremities, satisfaction and dissatisfaction respectively. Therefore, a performance exceeding the pre-purchase expectations leads to customer satisfaction and, in contrast, a performance lower than expectations results in dissatisfaction.

However, the unidimensional nature of satisfaction has been challenged by research in the quality management literature, having at its root the motivation-hygiene theory proposed by Herzberg, Mausner, and Snyderman (1959) in the context of job satisfaction, whereby satisfaction and dissatisfaction were considered the extremes of two distinctive continua. Based on Herzberg, Mausner, and Snyderman's (1959) two-factor theory, Kano et al. (1984) were the first to devise a multi-factor structure that encompasses the effect of service attributes on customer satisfaction, comprising factors that act in both the satisfaction and the dissatisfaction continua. Nonetheless, in the quality management literature, Kano et al.'s (1984) model, despite having five quality dimensions, is usually adopted as a three-factor model (Ting and Cheng 2002).

The three-factor theory has only recently gained momentum and consensus among researchers in the customer satisfaction domain (Anderson, Fornell, and Mazvancheryl 2004; Füller and Matzler 2008; Oliver, Rust, and Varki 1997), and much more recently in production research (Joung and Kim 2021). As reported by Füller and Matzler (2008), the reasons could lie in the support it found during the 90s by studies identifying asymmetric effects of product (e.g. Mittal, Ross, and Baldasare 1998) and service (e.g. Johnston 1995) attributes on overall satisfaction and its adoption by popular writers of that time. Exploring the structure of the three-factor theory of customer satisfaction, as reported by Matzler and Sauerwein (2002), it refers to three specific elements:

- Basic elements: basic factors are the backbone of the product/service offering and are essentially expected by the customers; however, their fulfilment is an insufficient condition towards satisfaction. The relationship between these factors' performance and satisfaction is asymmetric since high-level performance implies a lower gain in terms of overall satisfaction than low-level performance.
- Performance elements: this set of elements lies in both satisfaction and dissatisfaction continua: if performance is high (low) it can lead to satisfaction (dissatisfaction). Thus, the relationship between performance and overall satisfaction for this kind of feature is both symmetric and linear.
- Excitement elements: these factors can be a source of satisfaction if fulfilled, but their absence does not lead to dissatisfaction. There is an asymmetry in the relationship between overall satisfaction and attribute performance. Indeed, a low level of performance has a lower effect on satisfaction compared to a high level of performance for factors in this set.

The reasoning and articulation revolving around the three-factors model do not only provide a useful structure for academic researchers, but they also have meaningful implications when applied to managerial practices (Matzler and Hinterhuber 1998). In this respect, if we look at this classification schema from both the service marketing and operations management perspectives, as argued by Rust and Huang (2012) it could be difficult for organisations to embed excitement factors improving customer satisfaction, while simultaneously limiting financial expenses. Indeed, as expressed by Rust and Huang (2012), *service productivity often involves a tradeoff, with better service typically requiring more labour intensity, lower productivity, and higher cost* (Rust and Huang 2012, 47). However, challenging this argument, Wirtz and Zeithaml (2018) identify a set of core strategies that could lead organisations to conjointly achieve customer satisfaction and productivity gains. Thus, being able to classify a factor through the classification schema provided by Matzler and Hinterhuber (1998) can potentially help researchers understand their wider impact on companies' operations and strategies. Yet, to the best of the authors' knowledge, no studies have tried to examine the impact – in terms of overall satisfaction with the service offering – of the introduction of AI-empowered services in firms' operations. This is also apparent after running an advanced search of Scopus that led to the identification of 7 scientific outputs that do not deal specifically with production or operations management. Section 2.3.1 puts forward arguments to classify service robots in the three-factor model of customer satisfaction.

2.3.1. AI-empowered service operations in the three-factor model of customer satisfaction and hypotheses development

In this section we build on the three-factor framework of customer satisfaction (Matzler and Sauerwein 2002) to examine AI-empowered service operations from two different angles: service operations innovation and human–robot interaction. In innovation management literature, the introduction of either AI or a new technology-empowered service is likely to provide a competitive advantage to the firm introducing them (e.g., Mariani et al. 2022; Zahra, Nash, and Bickford 1995). Conceptually, AI-empowered service operations can be considered as a complex innovation (de Kervenoael et al. 2020) since they not only provide a new or improved service delivery method (technological element), but also modify the division of work within the service firm and the way the firm promotes itself. As such, the introduction of AI in service operations could have a positive impact on firm performance, especially on a non-financial performance indicator such as customer satisfaction. This line of reasoning is supported by extant studies in service research where the sense of novelty and uniqueness perceived by the service customer during the interaction with the robot can help co-create the service that can exceed customer expectations (Stock and Merkle 2018) and, in turn, originate customer delight (Oliver, Rust, and Varki 1997). Indeed, mechanical AI in the form of service robots is expected to enhance the service delivery process (Ivanov and Webster 2020). This conceptual view has been empirically substantiated by other studies that found a positive and pleasant surprise – described as a 'wow factor' – associated with service customers' interaction with mechanical AI (Tung and Au 2018). Building on innovation management literature (Jung, Kim, and Lee 2014; Mariani, Machado, and Nambisan 2023; Zahra, Nash, and Bickford 1995), an AI-empowered service can be considered an excitement factor in the three-factor model of customer satisfaction. Accordingly, we put forward the following hypothesis:

Hypothesis 1: A positive customer interaction with mechanical artificial intelligence increases overall customer satisfaction with AI-empowered service operations.

Nonetheless, the interaction of customers with AI-empowered services might be subject to failures (Fan et al. 2020) and could generate negative reactions (Tung and Au 2018). Based on attribution theory (Miller and Ross 1975), customers might tend to attribute negative performance externally (e.g. to the AI-empowered service) and positive performance internally (e.g. the service customer) (Miller and Ross 1975). This has been found to hold across different settings (Moon 2003). Whenever an operations issue takes place during the interaction between a service customer and an AI-empowered service, the customer is more likely to attribute the responsibility of the operations issue to the AI-empowered service (e.g. the service robot), thus expressing dissatisfaction with the service provision. In light of this asymmetry in attribution behaviours, AI-empowered services could be seen as acting also in the dissatisfaction continua. Thus, we could possibly relate them to either 'performance factor' or 'basic factor' based on the magnitude of the effect. However, extant research on human–robot interaction has not found support for any self-serving bias. Conversely, researchers identified the opposite effect in multiple service contexts (Fan et al. 2020; Jörling, Böhm, and Paluch 2019), the reason potentially being that service customers perceive mechanical AI-empowered services as social entities (van Doorn et al. 2017) and develop some sort of relationship with them (Tung and Au 2018). Accordingly, service customers are more likely to attribute the responsibility of a negative service performance internally (i.e. to themselves) (Moon 2003) than to the AI-enabled service. Accordingly, we can hypothesise that:

Hypothesis 2: A negative customer interaction with mechanical artificial intelligence does not significantly affect overall customer satisfaction with AI-empowered service operations.

3. Methodology

3.1. Data collection and empirical setting

As far as the empirical setting is concerned, the study takes into account consumers' online comments related to AI-empowered delivery services (e.g. service robots used for delivery service within the firm) deployed in hotel operations. Indeed, on the one hand, as suggested by extant research (see Borghi and Mariani 2021) online reviews represent a powerful means to record guests' perceptions of technological diffusion. On the other hand, hotels are considered among the type of businesses pioneering this novel service interaction (Tussyadiah 2020) where AI-empowered delivery services are currently the most adopted and homogenous type of service interaction (Millward 2018).

To identify relevant companies for our empirical sample, we followed the sampling methodology described and suggested by Inversini et al. (2010). Accordingly, comprehensive online research has been conducted using the keyword 'hotel' coupled with a series of keywords pertaining to AI-empowered delivery services (see Ivanov, Webster, and Berezina 2017). The preliminary set of hotels obtained during this first data collection step has been carefully scrutinised. Indeed, we triangulated different sources, namely hotel website, social media and review platform accounts, hotel news and hotel annual reports, to gather additional information about the company itself, especially in relation to the deployment of AI-empowered delivery services. After this further research, we selected only hotels whereby the deployment period of AI-empowered services was identifiable and that had a TripAdvisor account. We chose to focus on TripAdvisor due to its acknowledged international popularity as an online review platform (Bi et al. 2019). Thus, this allowed us to obtain a final sample of 35 hotels. In line with extant research (e.g. Tuomi, Tussyadiah, and Stienmetz 2021) the businesses recognised are located in two continents: America and Asia. Having selected the sample of hotels, we collected all the online reviews posted on TripAdvisor for each firm. Furthermore, we leveraged the automatic translation function provided by TripAdvisor to homogenise the language of the sample to English. More specifically, referring to the features collected, for each online review we captured verbal, reputation and quantitative features, namely the text of the review and the provided rating, as well as features related to the reviewer profile, for instance, their level of experience in the reviewing platform. Moreover, a set of metadata, at the hotel level, made available on TripAdvisor, were collected, such as the star rating and chain information to account for potential heterogeneity at the business level.

If the information was not found in the hotel's TripAdvisor profile, we searched the different sources collected during the data triangulation phase at the hotel level. All in all, 51,597 online reviews were collected but only 19,762 have been retained for the econometric analyses. This is because the latter refers to the online reviews written after the deployment of AI-empowered delivery services in hotel operations.

3.2. Analytical strategy and model selection

Regarding our analytical strategy, we leveraged the technique devised by Brandt (1987), namely penalty–reward contrast analysis (PRCA). According to extant research (e.g. Albayrak and Caber 2013) this analysis provides reliable and consistent outcomes when dealing with customer satisfaction data. In addition, as portrayed by Bi et al. (2020), it can be used effectively with consumer online review data. According to Brandt (1987), PRCA allows researchers to test the relationship between two constructs using different performance thresholds (i.e. positive and negative). In econometric terms, this translates into a regression analysis including dummy variables for identifying different performance levels related to the specific attribute analysed (Albayrak and Caber 2013).

More specifically, taking into account the ordinal and discrete nature of our dependent variable (Overall_Experience_Score), we decided to leverage an ordinal regression approach (Agresti 2010). Indeed, this approach helps researchers to account for the 'ceiling' and 'floor' effects displayed by econometric models using ordinal categorical indicators as dependent variables (Agresti 2010). Accordingly, following the lead of Godes and Silva (2012), we selected the logistic function for modelling the distribution of the error terms. Therefore, we estimated the following econometric model specification:

$$\begin{aligned} &\mathit{Overall\_Experience\_Score}^{*} \\ &\quad = \beta_0 + \beta_1 \text{AI-empowered\_delivery\_service\_Pos} \\ &\qquad + \beta_2 \text{AI-empowered\_delivery\_service\_Neg} \\ &\qquad + \beta_3 \mathit{Average\_Observed\_Score} + \beta_4 \mathit{Absence\_ID\_Details} \\ &\qquad + \beta_5 \mathit{Written\_Reviews} + \beta_6 \mathit{Submission\_Mobile} \\ &\qquad + \beta_7 \mathit{Sentiment\_Polarity\_Overall\_Score} \\ &\qquad + \beta_8 \mathit{Review\_Length} + \beta_9 \mathit{Firm\_Org\_Structure} \\ &\qquad + \theta_1' \mathit{Review\_Year} + \theta_2{}' \mathit{Firm\_Category} \\ &\qquad + \theta_3{}' \mathit{Firm\_Identifier} + \epsilon_{rh} \end{aligned} \tag{1}$$

where *Overall_Experience_Score** identifies the latent overall experience score provided by the online reviewer, ϵ_{rh} corresponds to the individual review error term and $\boldsymbol{\theta_i}$ and $\boldsymbol{\beta_i}$ represent the vector of coefficients and regression coefficients of the focal independent and control variables included in the model. The latter are described in Section 3.3.

3.3. Focal independent and control variables

As far as the focal independent variables are concerned, we created them using extant theorisation revolving around the application of Big Data analytics techniques to online review data (Alaei, Becken, and Stantic 2019; Bi et al. 2019; Mariani and Baggio 2021). In particular, we associated the perceived performance of AI-empowered delivery services with the polarity score obtained from the piece of text of the online review dealing specifically with this innovative service provision. More specifically, the technique recommended by Bi et al. (2019) was used for identifying the fragments of text discussing AI-empowered delivery services, while the guidelines from Alaei, Becken, and Stantic (2019) on which sentiment analyser to deploy were followed for this specific task. As a result, we adopted the sentiment analyser method devised by Hutto and Gilbert (2014), namely VADER, for obtaining a reliable polarity score from the AI-empowered delivery services-related comment.

From the polarity score we created the two dichotomous focal independent variables associated with AI-empowered delivery services performance, as follows:

$$\text{AI-empowered\_delivery\_service\_Pos} = \begin{cases} 1, & \mathit{Sentiment\ AI\text{-}empowered\ delivery\ services\ comment} > 0 \\ 0, & \mathit{Otherwise} \end{cases}$$

$$\text{AI-empowered\_delivery\_service\_Neg} = \begin{cases} 1, & \mathit{Sentiment\ AI\text{-}empowered\ delivery\ services\ comment} < 0 \\ 0, & \mathit{Otherwis} \end{cases}$$

Therefore, in the presence of a positive evaluation of the AI-empowered services analysed, *AI-empowered_delivery_services_Pos* (reward variable) is equal to 1, whereas, for a negative evaluation of the abovementioned service, *AI-empowered_delivery_services_Neg* (penalty variable) is equal to 1 in the econometric models. Examples of this binary variable can be found in Appendix 1. Furthermore, to associate AI-empowered delivery services with a specific category in the three-factor model, in line with the recommendation of Albayrak and Caber (2013), we leveraged Lin et al.'s (2010) classification scheme. Accordingly, AI-empowered delivery services can be categorised as:

- 'Basic element' if the penalty variable is significant while the reward variable is not significant;
- 'Performance element' if both the penalty and reward variables are significant;

Table 1. Variables' description.

Variable	Description
Overall_Experience_Score	It is the overall experience rating score provided by the online reviewer (ranging from 1 to 5) which captures her overall level of satisfaction with the service experience.
AI-empowered_delivery_service_Pos	It is a dummy variable equal to 1 if the online reviewer has provided a statement related to AI-empowered delivery services which is associated with a positive sentiment polarity score. It is equal to zero otherwise.
AI-empowered_delivery_service_Neg	It is a dummy variable equal to 1 if the online reviewer has provided a statement related to AI-empowered delivery services which is associated with a negative sentiment polarity score. It is equal to zero otherwise.
Control Indicators	
Average_Observed_Score	It represents the score observed by the online reviewer on TripAdvisor before submitting her review.
Submission_Mobile	It represents the device used by the online reviewer to submit her OR. In particular, it is equal to 1 if the reviewer has used a mobile device, and zero if desktop.
Written_Reviews	It denotes the number of reviews posted on TripAdvisor by the reviewer.
Absence_ID_Details	It is a dummy variable equal to 1 if the reviewer has not agreed to share either her age or her gender, 0 otherwise.
Sentiment_Polarity_Overall_Score	It is a continuous variable ranging from −1 (extremely negative) to +1 (extremely positive) which contains the sentiment polarity score associated to the entire text of the OR (Hutto and Gilbert 2014).
Review_Length	It denotes the number of words embedded in the OR.
Review_Year	It is a numeric variable which identifies the year when the OR was originally submitted. In the model it has been operationalised as a set of dummy variables (one for each year except for the first year of observations).
Firm_Identifier	It denotes a identifier that is unique to each firm in the dataset.
Firm_Org_Structure	It is a dummy variable that assumes the value of 1 when the firm belongs to a chain and zero otherwise.
Firm_Category	It refers to a categorical variable ranging from 1 to 5 which classifies firms based on their category.

Table 2. Descriptive statistics.

	Mean/proportion	SD	Min	Max
Overall_Experience_Score	4.393	1.007	1.000	5.000
AI-empowered_delivery_service_Pos	9.0%		0.000	1.000
AI-empowered_delivery_service_Neg	0.6%		0.000	1.000
Average_Observed_Score	4.347	0.213	3.400	5.000
Log(Written_Reviews)	2.326	2.094	0.000	11.703
Absence_ID_Details	74.5%		0.000	1.000
Sentiment_Polarity_Overall_Score	0.775	0.420	−0.996	1.000
Log(Review_Length)	4.304	0.658	2.890	7.431
Submission_Mobile	32.4%		0.000	1.000
Firm_Org_Structure	90.0%		0.000	1.000
Records	19,762			

- 'Excitement element' if the penalty variable is not significant while the reward variable is significant.

To ensure that our estimates portrayed reliable and robust results, as is clear from equation 1, we embedded a wide range of control variables in our regressions. The latter are in line with recent empirical works using online review data (e.g. Gao et al. 2018; Geetha, Singha, and Sinha 2017; Munzel 2016; Sridhar and Srinivasan 2012). In Table 1, a description of all the variables deployed in the econometric models is reported, while Table 2 reports their descriptive statistics. The logarithmic form of *Written_Reviews* and *Review_Length* is included in the regression models due to their high skewness.

4. Results

The results of the empirical analyses are reported in Table 3. In particular, the main model, namely Model 1, uses the entire sample of online reviews, while Model 2 is deployed on the sample of English online reviews. Exploring the coefficients related to the main focal dichotomous independent variables in the main model, on the one hand, *AI-empowered_delivery_services_Pos* portrays a significant and positive coefficient ($\beta_1 = 0.412$, $p < 0.001$). Thus, this indicates how a positive performance associated with an AI-empowered delivery service can increase the score posted by consumers for the overall experience and, in turn, their perceived overall satisfaction. Therefore, hypothesis 1 is supported. On the other hand, a negative but not significant coefficient ($\beta_2 = -0.212$, n.s.) is associated with *AI-empowered_delivery_services_Neg*. Accordingly, a negative performance of AI-empowered delivery services does not have a significant effect on the overall perceived satisfaction of a reviewing guest. This seems to suggest that service failure related to AI-empowered delivery services does not play a critical role in the mental process followed by service customers to produce their

Table 3. Estimation results regression models – dependent variable: Overall_Experience_Score.

	Entire sample model (1)	Sample English online review model (2)
AI-empowered_delivery_service_Pos	0.412***	0.392***
	(0.0569)	(0.0596)
AI-empowered_delivery_service_Neg	−0.212	−0.222
	(0.182)	(0.191)
Average_Observed_Score	0.269*	0.263*
	(0.252)	(0.262)
Absence_ID_Details	−0.0482	−0.0363
	(0.0394)	(0.0427)
Log(Written_Reviews)	−0.113***	−0.101***
	(0.00941)	(0.0103)
Submission_Mobile	0.0493	0.0356
	(0.0354)	(0.0388)
Sentiment_Polarity_Overall_Score	2.656***	2.686***
	(0.0401)	(0.0427)
Log(Review_Length)	−0.667***	−0.690***
	(0.0253)	(0.0272)
Additional controls:		
Dummy_Review_Year	YES	YES
Firm_Org_Structure	YES	YES
Firm_Category	YES	YES
Firm_Identifier	YES	YES
Intercept-1	−4.499***	−4.554***
	(1.124)	(1.169)
Intercept-2	−3.438**	−3.472**
	(1.124)	(1.168)
Intercept-3	−2.070*	−2.109*
	(1.123)	(1.168)
Intercept-4	−0.210	−0.296
	(1.123)	(1.168)
Observations	19,756	17,163
Pseudo R^2	0.182	0.178
AIC	35,747.5	31,482.1
LR Chi2	7,929.1***	6,775.9***
Log Likelihood	−17,822.8	−15,690.1

Notes: Standard errors in parentheses. The first model (1) presents fewer data points than the figure mentioned in Section 3.1 due to missing values related to the calculated *Average_Observed_Score* variable. * $p < 0.1$, ** $p < 0.01$, *** $p < 0.001$.

overall experience ratings. Thus, we found support also for hypothesis 2. Moreover, combining the abovementioned main results with Lin et al.'s (2010) classification method described in Section 3.3, AI-empowered delivery services can be effectively categorised as *Excitement element* in the three-factor model of customer satisfaction. This fuels the idea that AI-empowered service operations can positively surprise guests acting in the satisfaction domain, whereas, when their performance falls below expectations, this does not significantly lead to dissatisfaction with the service experience. Besides, the coefficients of the control indicators included in the analysis are in line with recent empirical literature using online review data. All in all, the obtained results support the two main hypotheses put forward by the study.

To further understand the robustness of the outcome of the main analysis, we re-run the regression models using the sample of online reviews posted in English (Model 2). The outcomes are in line with the ones presented above for Model 1, supporting our main results.

5. Discussion

5.1. Summary of key findings

Extant production systems and operations management literature covering the service industries has taken a service provider perspective so far (Wang, Skeete, and Owusu 2021), but not a more holistic perspective considering also customers. We find that AI (namely service robots) plays a positive and significant role beyond mere productivity and that in service contexts customer interaction with mechanical AI influences overall customer satisfaction with AI-empowered service operations. In line with the hypotheses put forward, we find that a positive performance associated with an AI-empowered delivery service enhances the online scores posted by consumers for the overall experience and, in turn, their perceived overall satisfaction. On the other hand, service failure related to AI-empowered delivery services does not play a critical role in perceived overall satisfaction. Our findings contribute to advance both production and operation management research examining service firms (e.g. Wang, Skeete, and Owusu 2021) and service management research that has merely taken a descriptive (Ivanov et al. 2019) or correlational approach (Luo et al. 2021). Accordingly, it seems that the adoption of mechanical AI not only constitutes an effective pathway to achieve efficiency gains and organisational performance (e.g. Al-Surmi, Bashiri, and Koliousis 2022), but also a way to enhance customer satisfaction.

5.2. Theoretical contributions

This work makes several contributions to multiple streams of literature at the intersection of AI in service operations, service operations management, service production, evaluation of customer satisfaction with services, human–robot interaction and online review text analytics.

First, by evaluating the three-factor theory (Matzler and Sauerwein 2002) through a managerial lens, following the classification schema developed by Matzler and Hinterhuber (1998), the study's results highlight how service robots, and more generally AI-empowered service operations, can *effectively* be associated with differentiation strategies (Porter 1985). Thus, this finding quantitatively corroborates the qualitative results of Tuomi, Tussyadiah, and Stienmetz (2021) who, based on observation of businesses and interviews with service managers, found that service robots were used mainly to pursue novel differentiation strategies.

Second, this work makes an important contribution to the literature at the intersection of operations management and service marketing by extending the work of Talluri, Kim, and Schoenher (2013). Indeed, combining the study's findings with the claim of Rust and Huang (2012), who predict an increase in productivity related to the automation of service operations, we can argue that AI-empowered service operations can be seen as a means to conjointly achieve gains in customer experience, service quality and productivity. This implies that the introduction of service robots does not necessarily generate a trade-off between productivity and satisfaction (Rust and Huang 2012), but rather allows service firms to achieve *cost-effective service excellence*, namely service excellence at low unit costs (Wirtz and Zeithaml 2018). Efficiency, in this case, is tightly related to the sustainability of service operations and the capability of service firms to face unexpected and unpredictable macroenvironmental events (e.g. natural disasters, health crises, political crises, etc.) by leveraging AI to improve the resilience of service operations.

Third, to the best of our knowledge, this work represents the first study revealing the existence of an *asymmetrical relationship* between AI-empowered service operations overall and customer satisfaction with service, proxied by online review ratings. Indeed, we detect *asymmetric effects* of AI-empowered service operations on customer satisfaction with services; namely, a positive customer interaction with mechanical artificial intelligence contributes to an improvement in overall customer satisfaction with AI-empowered service operations, whereas a negative customer interaction with mechanical artificial intelligence does not influence the overall customer satisfaction with AI-empowered service operations. As such, we answer the call for empirical studies related to the impact of AI-empowered service operations (Ivanov et al. 2019; Tussyadiah 2020). More specifically, the study aims to bridge the gap in extant literature related to the understanding – in the post-service consumption phase – of the effect of AI-empowered service operations on overall customers' judgements in terms of satisfaction and quality with the service experience (Lu et al. 2020). Following the progress in the customer satisfaction literature in the service domain, the three-factor model of customer satisfaction is used for its superior explanatory power (e.g. Bi et al. 2020). The results, related to service operations management and innovation and attribution theory applied to the human–robot interaction, significantly emphasise how positive customer interaction with mechanical artificial intelligence outweighs the effect of negative interaction with mechanical artificial intelligence in relation to overall customer satisfaction with AI-empowered service operations.

Therefore, this study adds to conceptual and qualitative studies that suggest that AI-empowered delivery services generate delight for service customers (Ivanov et al. 2019; Stock and Merkle 2018; Tung and Au 2018) and enriches an exploratory study (Luo et al. 2021) that used mere correlational analyses to make sense of sentiment measures versus service ratings. In turn, it confirms insights stemming from innovation management literature (e.g. Jung, Kim, and Lee 2014; Zahra, Nash, and Bickford 1995). On the other hand, AI-empowered delivery services seem to not significantly act in the dissatisfaction domain, possibly reflecting the results obtained by researchers investigating the attribution of responsibility in situations of failure of AI-empowered service operations (Fan et al. 2020; Jörling, Böhm, and Paluch 2019). These results, to a certain extent, are at odds with what has been proposed by Xu, Stienmetz, and Ashton (2020), who predicted service operations' quality pitfalls when introducing mechanical AI in service firms' operations. As is clear from the study's findings, the potentially low variability associated with the introduction of mechanical AI in service firms' operations is outweighed by their novelty effect, which makes them an excitement factor in the consumers' eyes. That said, the observed effect might decay over time as mechanical AI becomes more widely used by service firms.

Last, different from other empirical studies leveraging survey and laboratory experiment data (i.e. Fan et al. 2020; Jörling, Böhm, and Paluch 2019), this work exploits online review data on a very large sample of service firms, adding to the nascent field employing electronic word-of-mouth to explain customers' perceptions of AI-empowered service operations (Borghi and Mariani 2021; Chevalier and Mayzlin 2006; Dellarocas, Zhang, and Awad 2007; Liu 2006). Accordingly, this work extends recent research revolving around the novel concept of *online robotic discourse* (Borghi and Mariani 2021) to capture customer satisfaction with AI-empowered service operations and very recent production research (Joung and Kim 2021) that has deployed online review data to categorise product features.

5.3. Practical implications

This study bears several practical implications that might be relevant for operations managers dealing with AI technologies.

First, by recognising the peculiar nature of production in the service industries (Vargo and Lusch 2004), this work originally develops a new method useful to track customer satisfaction with AI-empowered service operations. As underlined by Xu, Stienmetz, and Ashton (2020), service firms need to proactively collect and analyse customers' feedback on AI-empowered services and, more generally, AI-empowered service operations, to gain a better understanding of customer satisfaction with them. Among the plethora of possible data sources, social media seems to be a critical means to track the evolution of AI-empowered service operations (de Kervenoael et al. 2020) and manage the operations in real time. Thus, as far as we know, this is the first study specifically developing an analytical strategy to control the impact of AI-enabled operations in service firms. As such, the innovative methodology deployed in the manuscript could be leveraged by service operations managers to assess and monitor – in real time – the performance of AI-empowered service operations. This might be particularly critical in light of the sudden emergence of unexpected and unpredictable macroenvironmental events (e.g. natural disasters, health crises, political crises, etc.).

Second, AI-empowered services might not always be perceived as novel by future generations of service customers. For instance, ATMs attracted a lot of popularity when they were first introduced, but later became commoditised services; the same might happen with AI-empowered services once they become more affordable and easier to embed in service firms' strategy (Wirtz et al. 2018). Accordingly, the novelty effect associated with AI-empowered services might decay in the medium and long term, making them increasingly perceived as a basic or performance attribute in service firms' operations (Wirtz et al. 2018).

Therefore, service operations managers introducing AI into service operations should carefully reflect on the unique traits characterising the service operations and assiduously improve them following an incremental innovation trajectory. This would allow service firms' operations managers to maintain and defend a competitive position, as well as continuously satisfy service customers. For instance, one year after introducing robot butlers in their operations, EMC2 hotel managers in Chicago decided to create a specific menu that would be exclusively delivered by their service robots. This not only made service robots more popular among hotel guests, but also boosted the number of in-room dining deliveries, almost doubling them (Escobar 2018). This seems to fit with the firm's philosophy *At the intersection of art & science* for EMC2.

Last, this work engenders important implications for service firms' managers and especially for service operations managers dealing with unexpected and unpredictable macroenvironmental events such as natural disasters, health crises and political crises. More specifically, our study suggests that since AI-enabled services such as service robots have been found to positively influence customer satisfaction with AI-empowered service operations, it is likely that also in a high-touch service context, high-tech can significantly enhance customer satisfaction. As a response to the COVID-19 pandemic many high-touch service firms had to comply with social distancing measures (Zeng, Chen, and Lew 2020). The development of AI-empowered service operations in service firms like hospitality, medical and travel companies can guarantee a high level of cleanliness and sanitisation and limit human-to-human interactions, which could ultimately decrease the risk perceived by service customers. Interestingly, Chinese hotels have introduced delivery robots to provide non-contact food service to guests spending their quarantine period in the hotel facilities (Cuthbertson 2020). Clearly, the current and next generations of service firms' managers should increasingly engage with AI technology to make sure that their operations management is sufficiently flexible and agile to accommodate sudden changes in the macro environment and to allow them to be increasingly resilient during and in the wake of crises. Undoubtedly, AI will increasingly help service firms to restructure strategies and operations during and in the wake of extraordinary events.

5.4. Limitations

Despite extending scholarly knowledge at the intersection of AI in service operations, service operations management, service production and evaluation of customer satisfaction with services, this study presents some limitations that could be addressed in the future. First, despite using a sample of 35 American and Asian service firms that have pioneered and developed AI-empowered service operations, we only collected data for a specific service industry that has been redefined by AI: hospitality (Ruel and Njoku 2020). Future studies might collect and analyse data from other service industries to ensure that we can generalise our results to the service industries. Second, in our data collection we have relied mainly on a specific online review platform, namely TripAdvisor. To improve the generalisation of the results, researchers could expand the research design by including data from other platforms (e.g. Booking.com for the hospitality industry, Yelp for restaurants and TrustPilot for other services). Third, we only leveraged AI-empowered delivery services based on mechanical intelligence. Despite this being at the moment the most adopted type of AI, it would be interesting in future research to understand whether our results hold in different service settings deploying other types of AI, such as intuitive or empathetic intelligence. Fourth, researchers might want to go beyond the exploration of the direct effect of AI-empowered services on customer satisfaction, examining potential mediators and moderators of this relationship. This would not only improve scholarly knowledge of human–robot interaction, but help effectively single out the real impact of AI-empowered services on perceived satisfaction.

6. Conclusion

Based on the three-factor theory of customer satisfaction applied to online review data, this study explained to what extent customer interaction with mechanical artificial intelligence increases overall customer satisfaction with AI-empowered service operations. The findings reveal that the effects of customer interaction with mechanical artificial intelligence on customer satisfaction with service operations are asymmetric; positive customer interaction with mechanical AI (in the form of service robots) positively and significantly influences overall customer satisfaction with AI-empowered service operations, whereas negative customer interaction with mechanical AI does not significantly alter customer satisfaction. Taken together, these findings suggest that mechanical AI constitutes a key element of resilient AI-empowered service operations.

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Data availability statement

Data available on request from the authors.

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Appendix 1

Focal independent variable	Examples
AI-empowered_delivery_services_Neg = 1	‘During our stay [robot name] was not working, and that was disappointing.’ ‘Disappointed that the robot-powered bag storage was full when I wanted to use it.’ ‘My only regret is that we didn’t get a chance to use the robots.’ ‘I was upset I never got to use [robot name]!’
AI-empowered_delivery_services_Pos = 1	‘[The hotel] is a hi-tech and modern hotel with room service robot, made me feel very excited when I saw this robot walk around the hotel.’ ‘I was pleasantly surprised, my requested additional bottled water was delivered by [robot name].’ ‘Especially loved [robot name], your robot. My daughter was excited when [robot name] got on the elevator with her. She wanted to bring [robot name] home with us!’ ‘I especially liked [robot name] the hotel’s robot butler. [Robot name] was amazingly efficient.’