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The impact of service robots on customer satisfaction online ratings: The moderating effects of rapport and contextual review factors

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Abstract

Recent research has established a positive relationship between the use of service robots powered by artificial intelligence in hospitality firms and customer satisfaction online ratings, a particularly important form of electronic word of mouth. However, it is not clear if and how this relationship is augmented or diminished by moderating factors. In this study, we examined four potential moderators by using machine learning and natural language processing techniques to analyze 20,166 online reviews of hotels that had implemented service robots. We had four key findings. First, a positive service robot-satisfaction rating relationship was further enhanced by improved customer-service robot rapport during the service encounter. Second, higher customer effort focused on service robots in a review reduced the service robot-satisfaction rating relationship. Third, posting reviews using a mobile device (vs. other devices) showed higher satisfaction ratings. Finally, customers' prior experience in writing online reviews was unrelated to the service robot-satisfaction rating relationship. Taken together, these results suggest that service robots should be designed to be interactive and encourage customers to build rapport, for example, by service robots engaging in conversational flows. Moreover, customers should be nudged to use their mobile devices to post timely reviews on their positive human–robot interactions.

KEYWORDS

customer satisfaction, eWOM, mobile, online reviews, rapport, service robot

1 | INTRODUCTION

Service firms have been innovative in their deployment of new technologies, especially digital technologies, to drive productivity and improve the service experience (Beatson et al., 2007; Belanche et al., 2019; Wirtz & Zeithaml, 2018). Service robots, typically powered by sophisticated artificial intelligence (AI), are about to completely redefine the service experience (Huang & Rust, 2018, 2021; Pitardi et al., 2022; Wirtz et al., 2023, 2018), including tourist experiences (Tussyadiah, 2020). Examples of deployment of service robots range from helping customers access legal (Harashima, 2019) and financial services (Wirtz et al., 2023), to medical advice, healthcare services

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(Belanche et al., 2020), and even prostitution (Belk, 2022). Hospitality businesses have been among the fastest adopters of service robots (Alderton, 2018) to provide concierge and in-room services, and welcome guests and take luggage to rooms (Kim et al., 2022).

Despite the growing interest in service robots, the literature on the topic remains fragmented (Lu et al., 2020) and is largely conceptual in nature (Belanche et al., 2020; Mariani et al., 2022). Notable exceptions include Fuentes-Moraleda et al. (2020) who empirically investigated several hospitality contexts. They found that interactions with robots revolve around functional dimensions, such as reception, luggage and room services, and guests were satisfied and liked the robots if they delivered according to expectations.

However, empirical work on the effects of service robots on consumer responses in the postencounter stage is limited. This motivated Lu et al. (2020) to specifically call for more research on the influence of service robots on perceived overall service quality and customer satisfaction. Indeed, one of the most important outcomes in customer relationship management (CRM) is the ability of the service providers to satisfy their customers (Mithas et al., 2005). Thus, due to the increased use of service robots in settings that involve creating and maintaining customer relationships (Yam et al., 2021) it is critical to disentangle the relationship between service robots and customer satisfaction. This is especially important in hospitality settings where customers post their satisfaction using online ratings, which in turn are then critical determinants in other potential guests' visitation decisions (Xie et al., 2014). Furthermore, as our literature review shows, extant empirical work has largely focused on attitudinal and affective antecedents and consequences of customer interactions with service robots, and virtually no research has examined potential moderators of these relationships. Our study aims to fill this gap by addressing the following research question:

RQ What are the moderating variables influencing the effect of the presence of service robots on customer satisfaction online ratings?

This study employs a comprehensive framework, integrating contemporary theories that examine consumer–robot interactions, such as the service robot acceptance model (sRAM) (Wirtz et al., 2018) and construal-level theory (CLT; Trope & Liberman, 2003), and existing electronic word-of-mouth (eWOM) research and theorizations (e.g., Chevalier & Mayzlin, 2006; Gao et al., 2018). By doing so, we aim to examine potential moderating factors that may serve as indicators of cognitive processes and the consumer assessment immediacy. On the one hand, various cognitive judgments coexist alongside affect in driving satisfaction and these are central to understanding customers' consumption experiences (Oliver, 1997). On the other hand, the immediacy of the consumers' assessment can influence the intensity of their emotional responses (Ransbotham et al., 2019). As such, we make several contributions as we examine four potential moderating factors of the relationship between customers' interaction with service robots and customer satisfaction online ratings. They are (1) rapport developed during the service interaction, (2) customer effort focused on a service robot when writing an online review, (3) device deployed for writing and posting a review (mobile devices vs. others), and (4) the customer's prior online review experience.

Our study goes beyond the typical demographic characteristics of customers by including moderators that can be considered manifestations of cognitive processes (i.e., rapport during the service encounter and effort focused on the service robot when writing a review), and the immediacy of the assessment (proxied by the device deployed to post the review, with mobile devices being considered the most immediate access tool). By examining the effect of these moderators, our study helps extend and develop emerging theories in the field of service robots—namely the service robot adoption model (Wirtz et al., 2018). Furthermore, we make a methodological contribution by refining and empirically testing how user-generated comments can be used to inform decision-making on the effectiveness of service robot deployment. This novel approach to user-generated content extends the satisfaction and eWOM literature.

The remaining sections of this article are organized as follows: Section 2 reviews the literature on service robots and discusses their impact on customer satisfaction, revealing a theoretical gap relating to potential moderators of the relationship between customer interactions with service robots and subsequent customer satisfaction. Here, we also discuss key constructs, their hypothesized relationships and develop a conceptual model. Section 3 details our research method and Section 4 presents the analysis and findings. Finally, Section 5 synthesizes our findings, discusses the theoretical and methodological contributions, managerial implications, as well as the research limitations and further research opportunities.

2 | LITERATURE REVIEW

2.1 | The rise of service robots

Service robots are "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers" (Wirtz et al., 2018, p. 909). Wirtz et al. (2018) established three design attributes helpful in differentiating service robots: task orientation (i.e., social–emotional vs. cognitive-analytical tasks), anthropomorphism (machine vs. human-like appearance), and representation (physical vs. virtual service robots). For example, service robots can exist either in the physical realm (e.g., room service robots) or can be virtually represented (e.g., chatbots) (Lu et al., 2020).

The impact of service robots goes beyond the interaction with customers as they dramatically change the work of service employees and increase firm capabilities to provide services at lower costs (Wirtz et al., 2018). Wider impacts at a mesolevel (i.e., the market level, with service robots leading to an increase in industry concentration) and macrolevels (i.e., the wider society impact, leading to an increase in the standard of living but concerns over dehumanization and algorithm-caused biases) have also been explored at the conceptual level (e.g., Huang & Rust, 2018, 2022; Wirtz et al., 2023, 2018). Empirical evidence has shown that the types of intelligence robots possess can improve customer satisfaction in different types of firms, from the use of robots with mechanical intelligence for low-cost services, to robots with feeling intelligence for full-service providers (Schepers et al., 2022).

One of the reasons why service robots have become increasingly important in virtually all service sectors and attract increasing academic interest are their rapidly growing capabilities. These are driven by constant development and innovation in hardware (e.g., the physical components of service robots such as their bodies, sensors, chips, and cameras) and software and AI (e.g., image processing, natural language processing, and machine learning) (Bornet et al., 2021; Wirtz et al., 2018). We can expect this trend to accelerate as both physical and virtual service robots will increasingly be powered by generative AI (e.g., ChatGPT; Dwivedi, Kshetri, et al., 2023) and will also be delivered in the metaverse (Dwivedi, Hughes, et al., 2023).

These capabilities will make service robots increasingly effective in maintaining customer relationships where communication, understanding, interaction, and experience are important (Huang & Rust, 2021, 2022). Robots have evolved from doing repetitive tasks to performing less structured frontline interactions with their human customers. As such, service robots are increasingly used in settings that involve creating and maintaining customer relationships (Yam et al., 2021). As one of the most important outcomes in CRM is the ability of the service provider to satisfy their customers (Mithas et al., 2005), in the following sections we examine how service robots relate to eWOM and customer satisfaction.

2.2 | Online review ratings and eWOM

The literature on eWOM is vast and heterogeneous and spans a wide range of disciplines ranging from marketing, information management and computer science, to innovation management and finance (Babić Rosario et al., 2020). The exponential growth of social media and digital platforms has led to a proliferation of user-generated comments, especially in the form of online reviews. As suggested by the seminal study of Hennig-Thurau et al. (2004) on eWOM, online reviews allow customers to generate and share their personal judgments related to brands, firms, products, and services with an online community. In the marketing literature, online reviews are considered a core component of eWOM (King et al., 2014).

When posted in online communities, online reviews may focus on different features and factors, and display different layouts. Their content can be effectively summarized in three different sets of factors: reputation, social, and evaluation factors (O'Mahony & Smyth, 2010). First, reputation factors relate to reviewers' profile information, with gender, age, and home country being the most common metrics. Second, social factors entail platform-related mechanisms allowing online users and company managers to engage with online reviews. The two main variables examined are helpfulness votes and the responses of managers. Third, evaluation factors pertain to the review itself and can be distinguished between quantitative (e.g., ratings and volume) and qualitative (e.g., review text and tags). The main indicator among the quantitative factors is the overall rating, often named "valence," that relates to a numeric score representing a reviewer's assessment of the overall experience (Xie et al., 2014). This measure has received particular attention by eWOM scholars as the cognitive processes that lead to customer satisfaction are reflected in such ratings and, therefore, are considered a good proxy of customer satisfaction (Engler et al., 2015).

2.3 | Service robots and customer satisfaction

Recent research has investigated the antecedents of customer satisfaction with service robots. Initial studies examined the physical appearance of robots (Grazzini et al., 2023; Murphy et al., 2017; Seo, 2022; Yam et al., 2021), the nature of interactions (e.g., heartwarming interactions; Nakanishi et al., 2020), and the functional, socio-emotional and relational factors that influence interactions (Fuentes-Moraleda et al., 2020). More recent studies suggest that customer satisfaction with service robots is higher when robot types align with a firm's relationship orientation (Chang & Kim, 2022).

The evolution of attitudes and feelings towards service robots in the pre- and postservice encounter stage have been examined in a number of studies. For example, Tung and Au (2018) found that customers shift from fear and insecurity before an interaction, to trust and comfort emerging postexperience when an interaction is perceived as successful. Chuah and Yu (2021) showed that when service robots express positive feelings (e.g., surprise or happiness), customers respond in kind. Furthermore, several studies found that interactions with service robots can have a positive effect on customer evaluations of hotel services and elicit positive emotions among guests (Borghi & Mariani, 2021), especially when service robots possess quality attributes, such as signature design, which can lead to higher levels of customer satisfaction (Luo et al., 2021; Tung & Au, 2018). Similar effects have been observed in other services settings (e.g., search, experience, and credence service settings) that convey distinct levels of perceived risk when using service robots (Park et al., 2021).

Studies have examined whether the gender of the robot has an impact on customer satisfaction. For example, customers expressed higher satisfaction when interacting with female service robots compared to male ones, but only when the robot was humanized (Seo, 2022). Further, this study showed that the degree of pleasure customers experience from the interaction mediates the relationship between robot gender and satisfaction. Additionally, customer attitudes towards service robots in hotels were influenced by gender roles in society, with men showing more interest in technical knowledge related to service robots and women were more interested in establishing personal relationships (Ayyildiz et al., 2022).

However, some studies suggest that service robots may generate negative attitudes if they are perceived as a threat. Customers may express fear due to macroenvironmental effects, such as job displacement or specific concerns related to privacy (Gretzel & Murphy, 2019; Pitardi et al., 2022). However, evidence shows that when customers perceive that service robots are used for service augmentation instead of replacement of staff, these negative attitudes can be mitigated (McLeay et al., 2021). In addition, despite advancements in the implementation of service robots, scholars have found that a lack of humanization of the design and the speed of responses service customers receive from robots can reduce customer satisfaction (Luo et al., 2021).

Finally, customer characteristics can influence attitudes toward service robots. Ayyildiz et al. (2022) reported that Generation Y and Z were more interested in services provided by robots, while Generation X believed that robots offered poor service due to their lack of social skills.

To summarize, empirical findings show that, in most cases (and when service robots meet customer expectations), there is a positive relationship between the deployment of service robots and customer satisfaction, and this relationship holds in offline (Chang & Kim, 2022; Seo, 2022) as well as online settings (Borghi & Mariani, 2021; Mariani & Borghi, 2021; Söderlund & Oikarinen, 2021). As firms generally only deploy service robots that can meet or exceed customer expectations, we suggest that this positive relationship is common and represents the baseline for our study. Extant research has mostly focused on attitudinal and affective antecedents and consequences related to service robots, and limited attention has been given to potential moderators; something that has been shown to be important when other service delivery technologies were introduced in the past (e.g., Dabholkar & Bagozzi, 2002; Weijters et al., 2007). Table 1 summarizes the main findings of the studies cited in this section.

In the following sections, we review the literature with a focus on our four potential moderators of the service robot–customer satisfaction online rating relationship that can be considered manifestations of cognitive processes and the immediacy of the assessment. Our hypothesized relationships are shown in the conceptual model in Figure 1.

2.4 | Moderator 1: Rapport between the customer and the service robot

Recent conceptual work has synthesized the literature and proposed a comprehensive model of the sRAM, with trust and rapport as important relational moderators of robot acceptance (Wirtz et al., 2018). The role of trust (e.g., Tussyadiah et al., 2020) and the related construct of warmth (Belanche et al., 2021) have been tested empirically in several settings. However, the role of rapport remains unexplored.

Wirtz et al. (2018) suggested that "rapport can be characterized as the customer's perception of an enjoyable interaction with a service robot, as well as a personal connection between the customer and the robot" (p. 918). Furthermore, rapport-building strategies have been shown to be important for improving both customer–employee (Gremler & Gwinner, 2000) and customer–service robot interactions (Seo et al., 2018), and can lead to higher levels of engagement (Tung & Au, 2018). These studies suggest that better rapport between customers and service robots can lead to higher levels of customer satisfaction. Therefore, we advance that:

> **H1.** A higher level of rapport between a customer and a service robot increases the positive effect of the presence of a service robot on the customer satisfaction online rating.

2.5 | Moderator 2: Customer effort focused on service robot when writing a review

When commenting about specific service attributes, consumers tend to emphasize and recall the attributes that have had a greater impact on their judgment. For example, in the eWOM literature the length of user-generated comments has been associated with the concept of reviewing effort, and the longer the comment, the greater the reviewing effort (Chevalier & Mayzlin, 2006). Building on this, Zhao et al. (2019) provided empirical evidence of the existence of a negative and direct relationship between the length of a reviewer's comment and their overall evaluation of the service experience. In other words, the longer the comment, the lower the customer's satisfaction with the service (Zhao et al., 2019). This is because, as suggested by Xu and Li (2016), consumers tend to post longer and more detailed descriptions of negative aspects stemming from service consumption. This tendency at the individual service attribute level may well extend to the overall evaluation of service robots. In our study, we extend this line of argument to the customer effort focused on service robots in their reviews, that is, the proportion of the text in their reviews relating to robots. Therefore, we argue that:

> **H2.** A higher level of reviewing effort focused on service robots reduces the positive effect of the presence of a service robot on the customer satisfaction online rating.

2.6 | Moderator 3: Device deployed to post the review

eWOM is not created and consumed in the same manner across devices, and the type of device can shape eWOM (Ransbotham et al., 2019). For example, user-generated content submitted via mobile devices has been found to systematically differ in the evaluation of service experiences (Melumad et al., 2019). As suggested by Melumad et al. (2019), this is due to the more pronounced real-time nature associated with mobile devices. Here, CLT (Trope & Liberman, 2003) provides a theoretical ground to hypothesize that the immediacy of writing a review after a robot service encounter can play a critical role. More specifically, CLT argues that customers will use a higher level of construal to represent an object, person or event as the temporal distance increases (Trope & Liberman,

TABLE 1 Summary of key studies and their findings.

Studies	Theories	Context	Main findings
Grazzini et al. (2023)	• Expectation disconfirmation theory. • Social cognitive theory.	Hotels	• High (vs. low) robot human-likeness led to more negative customer responses due to disconfirmed expectations.
Ayyildiz et al. (2022)	• Generational theory.	Hotels	• While hotel guests were uncertain about their attitudes towards the presence of robots in daily life, they had positive attitudes towards services delivered by robots. • No difference was found in the attitudes of guests towards service robots based on the guests' country of origin.
Chang and Kim (2022)	• Congruity theory.	Hotels	• Different types of service robots (functional vs. social) were evaluated based on the relationship orientation of the firm (communal vs. exchange orientations). • Enhanced satisfaction arose when functional service robots were congruent with an exchange-oriented approach. • Social robots received more favorable evaluations when they aligned with a communal orientation.
Pitardi et al. (2022)	• Theory of mind.	Healthcare	• Customers felt less embarrassed during a potentially embarrassing service encounter when they interacted with a service robot compared to a human employee. • Service robots' reduced agency (e.g., inability to make moral or social judgments) explained this effect.
Seo (2022)	• Uncanny valley theory.	Hotels	• Female service robots elicited more pleasure and higher satisfaction compared to male service robots.
Söderlund and Oikarinen (2021)	• Theory of mind.	Users of virtual agents in services	• Perceived virtual agent's effort was associated with higher customer satisfaction. • Agency, emotionality, and morality of virtual assistants were antecedents of perceived humanness, and the latter was found to be positively related to customer satisfaction.
Borghi and Mariani (2021)	• Innovation management theories.	Hotels	• The deployment of service robots had a positive effect on customer satisfaction.
Chuah and Yu (2021)	• Uncanny valley theory.	Sophia the robot	• Expressions of surprise and happiness of service robots had a positive effect on consumers.
Luo et al. (2021)	• Uncanny valley theory. • Media equation theory.	Hotels	• Robot quality attributes (i.e., signature design) and operations' attributes related to the amenities offered in the hotels (i.e., rooms, reception, luggage, dining) correlated with customer satisfaction.
Yam et al. (2021)	• Theories of anthropomor-phism.	Field study—robot-staffed hotel	• Anthropomorphism led to higher customer satisfaction. • Robot's perceived experience (i.e., emotion) and not agency mediated this effect.
Fuentes-Moraleda et al. (2020)	• Service robot acceptance model (sRAM).	Hotels	• Functional dimensions (i.e., ease of use, usefulness and adherence to social norms) were the elements that consumers mentioned most from their experiences with service robots.
Nakanishi et al. (2020)	• There is no reference to a specific theory.	Hotels	• Social robots engaging in heart-warming interactions (e.g., using warm words such as "Good morning," "We welcome you") improved customer satisfaction.
Gretzel and Murphy (2019)	• Consumer culture theory. • Technology ideology framework.	Websites and social media platforms	• Different technology ideologies (i.e., techtopian, green luddite, work machine, and techspressive) were represented when discussing social robots. • Conceptualizations of service robots as beings that deserve rights add to the complexity of the discourse, tapping into notions of social justice and equity.

(Continues)

TABLE 1 (Continued)

Studies	Theories	Context	Main findings
Tung and Au (2018)	• Usability, Social Acceptance, User experience, Societal impact evaluation framework.	Hotels	• Robotic embodiment and human-oriented perceptions impacted consumer experiences with service robots. They allowed guests to establish a "relationship" with service robots.
This paper	• sRAM, construal level theory and existing electronic word-of-mouth research and theorizations.	Hotels	• Customer-service robot rapport during the service encounter and posting reviews using a mobile device (vs. other devices) increased the positive service robot-satisfaction rating relationship. • Higher customer effort focused on service robots in a review reduced the service robot-satisfaction rating relationship. • Customers' prior experience in writing online reviews was unrelated to the service robot-satisfaction rating relationship.

Note: Studies are listed in reverse chronological order; studies published in the same year are listed in alphabetical order.

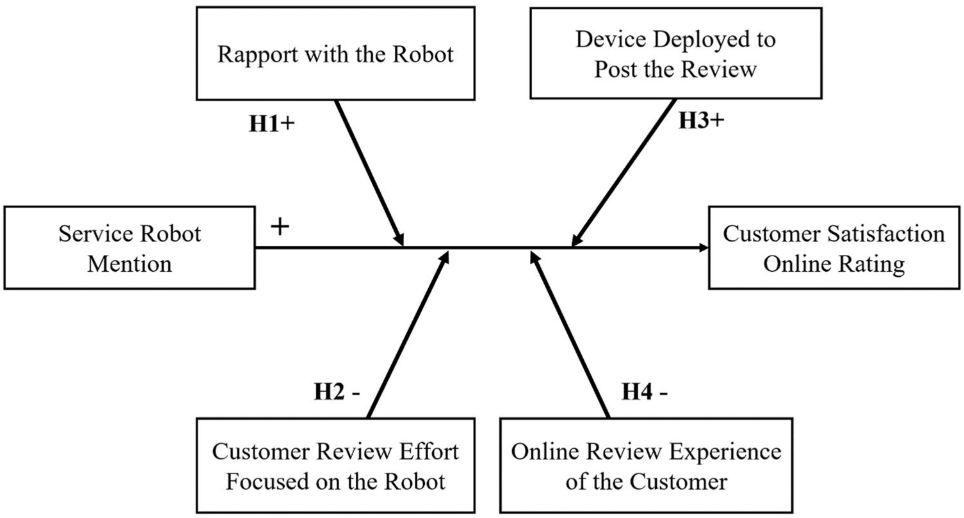

FIGURE 1 Conceptual model.

2003). High (vs. low) temporal distance translates into lower (vs. higher) levels of temporal immediacy between the observer and the event (Kim & Youn, 2019). High temporal immediacy has also been shown to positively influence social media content impact on engagement and persuasion (Perez-Vega et al., 2016). Furthermore, leveraging "fuzzy-trace theory" of processing (e.g., Reyna, 2012), Melumad et al. (2019) suggest that reviewers using mobile eWOM focus on the gist representation of their experience. Adding to this, greater spontaneity, combined with less reflection, increases the intensity of emotional responses in online reviews posted using mobile devices (Ransbotham et al., 2019).

In summary, the use of mobile devices can be seen as an amplifier of either positive or negative service experiences. Recent empirical evidence supports this reasoning and shows how the relative ratio of extremely positive and negative online reviews posted using mobile devices is considerably higher than that of reviews posted through nonmobile devices (e.g., Mariani et al., 2019). Thus, since the mention of service robots in the evaluation of the service experience generally has a positive impact on satisfaction, we might argue that this effect is amplified when the reviewer uses a mobile device to post their evaluation. Therefore, we hypothesize that:

> **H3.** A mobile device (vs. a nonmobile device) increases the positive effect of the presence of a service robot on the customer satisfaction online rating.

2.7 | Moderator 4: Customer's prior online review experience

Reviewer characteristics have been shown to play a role in online review ratings. The experience customers have is of particular importance due to the intangible and heterogeneous nature of services (Zeithaml, 1981). Furthermore, experts evaluate services differently from novices (Bendapudi & Berry, 1997) and provide more useful and objective information to others (Goes et al., 2014). Experts, by definition, have experienced a larger variety of services and therefore tend to be more knowledgeable and objective in their evaluation. Thus, the perception of superior service performance is less likely for this group of reviewers. Empirical evidence confirms that expert reviewers are more critical in their evaluations and more prone to leaving lower ratings (Gao et al., 2018). Therefore, extending this argument to service robots we advance:

H4. A higher level of customer's prior online review experience reduces the positive effect of the presence of a service robot on the customer satisfaction online rating.

3 | METHODS

In this study, we examined customer online reviews that mention service robots in hotel contexts. Hotels have been pioneers in the use of robots in customer service (Tussyadiah, 2020) and online reviews represent a powerful means to track the customer experience with service robots in hotel operations (Borghi & Mariani, 2021). This reasoning is supported by the growing body of literature on the topic (e.g., Calero-Sanz et al., 2022; Huang et al., 2021; Tung & Au, 2018; Yu, 2020).

3.1 | Data collection

Our research design leveraged a big data analytics approach (Stylos et al., 2021) and our data were collected in two main stages. In Stage 1, we identified a set of hotel companies that deployed service robots in their day-to-day operations. We followed the lead of Inversini et al. (2010) and conducted a set of search queries using Google as a browser. The search terms were created by combining the search term "hotel" with functions that have been commonly associated with the deployment of robots in hotel operations. According to Ivanov et al. (2017), the main examples of these functions include: front desk robots, concierge robots, delivery robots, vacuum cleaning robots, porter robots, room assistant robots, housekeeping robots, cleaning robots, and laundry robots. Therefore, we used these functions as search terms (Ivanov et al., 2017).

For each hotel identified through the initial search, we gathered further detailed research on hotel-specific information related to the use of robots. This research included collecting and analyzing data from sources such as annual reports, hotel websites, hotel social media, profiles and hotel news featured in traditional media. The process included scanning each source and searching for specific references that focused on the deployment of service robots.

After these individual searches, we adopted two inclusion criteria to derive our final sample: (1) the company had clearly reported the timeframe related to the robot deployment, and (2) had an account on the reviewing platform TripAdvisor. The latter is considered the largest online reviewing platform and the most popular among studies leveraging online reviews (Ali et al., 2021). Following these criteria, the final sample for our study consisted of 19 international hotels.

In Stage 2 of our data collection, we collated individual online reviews. For each of the 19 hotels, we accessed their TripAdvisor public profile and collected all the online reviews posted. The complete set of consumer opinions resulted in a data set of 49,209 online reviews. Consistent with past research, we only retained online reviews originally posted in the English language (e.g., Zhao et al., 2019) and reported travel type (i.e., business vs. leisure) (e.g., Fuentes-Moraleda et al., 2020). Furthermore, we removed reviews that were posted before each specific hotel had introduced service robots in its operations. This screening resulted in a final data set of 20,169 reviews for our analysis. In addition to the metadata related to each single online review (reviewer name, timestamp, etc.), we also obtained the hotel metadata from its TripAdvisor profile page (e.g., star rating and whether it belonged to a chain).

Finally, during our analysis, we found missing values in the observed average hotel rating variable for three reviews. That is, these three customers could not observe any prior average rating on the hotel's TripAdvisor page before submitting their reviews. Due to the extremely low number of records (three) we decided to remove these observations from the analysis without deploying any missing data imputation technique. That is, the final data set included in our econometric models was 20,166 reviews.

3.2 | Variables

Our dependent variable is the customer satisfaction online rating (Zhao et al., 2019), labeled as *Customer Satisfaction Rating*, which is proxied by the overall review rating associated with an online review. As suggested by extant eWOM research (e.g., Mariani & Borghi, 2021), the overall review rating is determined by the level of customer satisfaction with the service and, therefore, considered a good proxy of customer satisfaction. On TripAdvisor, the reviewer can rate their experience using an ordered scale ranging from 1 = "Terrible" to 5 = "Excellent."

The independent variables included in our study were inferred from the online review metadata and combined with text analytics techniques. The main independent variables were operationalized as follows:

3.2.1 | Service robot mention

To infer whether a customer mentioned "service robot" in their review, we followed Tung and Au's (2018) approach and searched in the online review text for the keyword "robot" and the robot's name as used by the hotel. Based on the results of this search, we created a binary indicator using the following rule:

$$\text{Service robot mention} = \begin{cases} 1, & \text{if keywork "robot" or robot name in review text} \\ 0, & \text{otherwise} \end{cases}.$$

3.2.2 | Rapport with robot

Recalling a service provider's name can be viewed as having built rapport (Kim & Baker, 2017). Therefore, we proxied the establishment of rapport between the service customer and the robot by establishing whether the customer used the robot's proper name in the post. Therefore:

$$\text{Rapport with robot} = \begin{cases} 1, & \text{if robot name in review text} \\ 0, & \text{otherwise} \end{cases}.$$

3.2.3 | Customer review effort focused on the robot

Each online review can be described as a combination of topics which can be identified by a series of keywords (Bi et al., 2019). Following the lead of Bi et al. (2019), we labeled the set of sentences in the online review text that contained either the search term "robot" or the robot's name as "robot statement." To understand the customer's focus on the service robots in their review, we followed Mariani and Borghi's (2022) approach of calculating the ratio between the length of the robot-related statement and the total length of the entire review text:

$$\text{Customer review effort focused on the robot} = \frac{\text{length robot statement}}{\text{length total review text}}.$$

3.2.4 | Device deployed to post the review

Following the lead of Grewal and Stephen (2019), we proxied the variable submission device by the submitted "via mobile" label. Accordingly, a binary variable was obtained:

$$\text{Device deployed to post review} = \begin{cases} 1, & \text{access via mobile} \\ 0, & \text{otherwise} \end{cases}.$$

3.2.5 | Online review experience of the customer

We proxied the reviewer experience by the number of reviewer contributions a customer had posted on TripAdvisor (Gao et al., 2018):

$$\text{Online review experience of the customer} = \text{No. of reviewer contributions in TripAdvisor}.$$

In addition to our dependent and independent variables, we used a wide range of controls derived from the customer review and hotel level (e.g., its star rating and whether it is part of a chain). The control variables are described in Table 2, while Table 3 includes the sample's descriptive statistics.

3.3 | Estimation technique and empirical model

We chose to use an ordered logit model to test our hypotheses as the dependent variable is ordinal (Agresti, 2010). Our econometric model specification is constructed as follows:

$$\begin{aligned} y^*_{ij} = {} & \beta_0 + \beta_1 \text{Service robot mention}_{ij} \\ & + \beta_2 \text{Service robot mention}_{ij} \times \text{Rapport with robot}_{ij} \\ & + \beta_3 \text{Service robot mention}_{ij} \\ & \times \text{Customer review effort focused on the robot}_{ij} \\ & + \beta_4 \text{Service robot mention}_{ij} \\ & \times \text{Device deployed to post the review}_{ij} \\ & + \beta_5 \text{Service robot mention}_{ij} \\ & \times \text{Online reivew experience of the customer}_{ij} \\ & + \theta' Z_{ij} + \epsilon_{ij}. \end{aligned}$$

where Z_{ij} and ϵ_{rh} relate to the control variables and the individual error term respectively, while y^*_{ij} represents the latent realization of the customer satisfaction rating. In addition to the direct association between service robot mention and customer satisfaction, we included our hypothesized four moderators in the model through the coefficients β_2, β_3, β_4, and β_5.

4 | FINDINGS

Our findings are presented in Table 4. We can see that customers who mention service robots in their reviews are significantly more satisfied (β_1 ranges from 0.27 to 0.54, $p < 0.001$), which is consistent with extant research (e.g., Chang & Kim, 2022; Mariani & Borghi, 2021; Seo, 2022; Söderlund & Oikarinen, 2021).

Model 1 (see Table 4) tests the hypothesized moderation effect of customer rapport on customer satisfaction online rating. The model shows that rapport moderates positively and significantly ($\beta_2 = 0.49$, $p < 0.001$). That is, a higher rapport between the customer and service robot strengthened the positive effect of service robots mention on customer satisfaction, providing support for H1.

Model 2 adds customer review effort focused on the robot as our second moderating variable. The model shows that a stronger customer focus on the service robot in their review, resulted in a weakened positive robot-satisfaction rating relationship ($\beta_3 = -0.60$, $p < 0.05$). This finding supports H2.

Model 3 examines the effect of the type of device used to post the review. As hypothesized in H3, we find that customers who used a mobile device showed a stronger robot–customer satisfaction rating relationship than customers who used other devices ($\beta_4 = 0.28$, $p < 0.01$).

TABLE 2 Control variables.

Control variables	Description
Review-level controls	
• Observed average rating	Overall hotel rating score observed by customers on the hotel's TripAdvisor page before they posted their own reviews (Sridhar & Srinivasan, 2012).
• Identity disclosure	Customer-provided demographic information on TripAdvisor (c.f., Gao et al., 2018). This variable is equal to 1 if a customer provided gender or age to TripAdvisor; it assumes the value of 0 otherwise.
• Travel type	Type of travel categorized into "group," "family," "solo," "couple," or "business" (Bi et al., 2020).
• Review length in number of words	Number of words included in the online review text.
• Year	Year when the online review was posted (Mariani & Borghi, 2022).
Hotel-level controls (c.f., Zhao et al. [2019])	
• Chain	Captures whether a particular hotel belonged to a chain. If yes, it assumes the value of 1, 0 otherwise.
• Star rating	Star rating of the hotel on an ordinal scale that ranges from 1–5 stars.
• Hotel ID	Unique identifier of each hotel included in the analysis. In the econometric analysis, it is operationalized using a set of binary variables.

TABLE 3 Descriptive sample statistics.

	Mean/ percentage	SD	Min	Max
Dependent variable				
• Customer satisfaction rating	4.26	1.04	1.00	5.00
Focal independent variables				
• Service robot mention	13.8%		0.00	1.00
• Rapport with robot	4.6%		0.00	1.00
• Customer review effort focused on the robot	0.03	0.09	0.00	1.00
• Device deployed to post the review	23.2%		0.00	1.00
• Log (online review experience of the customer)	2.15	1.87	0.00	11.70
Further control variables				
• Observed average rating	4.32	0.16	3.20	5.00
• Identity disclosure	29.0%		0.00	1.00
• Log (review length in number of words)	4.42	0.71	2.08	7.61
• Chain	99.3%		0.00	1.00
Number of observations	20,169			

Abbreviations: Max, maximum; Min, minimum; SD, standard deviation.

Model 4 includes customer online review experience as a moderator. The findings show an insignificant interaction effect ($\beta_5 = 0.01$, $p > 0.1$), rejecting H4. That is, the customer's prior review experience had no impact on the service robot-satisfaction rating relationship.

Finally, in Model 5 we test all four hypothesized moderating effects conjointly. The findings are consistent with those in Models 1 through to 4 and show that each significant moderating variable explains unique variance. Furthermore, the findings seem robust with consistent significance levels, directional effects and magnitude of impact. These findings provide further support for H1, H2, and H3. H4 remains rejected with a β of close to 0 (i.e., 0.01 in Model 4 and −0.03 in Model 5).

5 | DISCUSSION, IMPLICATIONS, AND FURTHER RESEARCH

Recent research established a positive relationship between the use of service robots in hospitality firms and customer satisfaction online ratings (e.g., Borghi & Mariani, 2021; Chang & Kim, 2022; Luo et al., 2021; Mariani & Borghi, 2021; Seo, 2022), a particularly important form of eWOM. However, it was not clear if, and how, this relationship is augmented or diminished by moderating factors. In this study, we examined four potential moderators: (1) customer–service robot rapport; (2) higher customer effort focused on service robots in a review; (3) submission device used to post a review; (4) customers' prior experience in writing online reviews. Our study tested hypotheses based on these moderating variables to understand their influence on the relationship between service robot deployment and customer satisfaction online ratings. We found the first three moderating effects to be significant and in the hypothesized direction, while the last was not significant. The implications of our findings for theory are discussed next.

5.1 | Implications for theory

This study makes several theoretical contributions to the field of service robots, service marketing, customer satisfaction and eWOM.

TABLE 4 Estimation results of ordered logistic models.

		Model 1	Model 2	Model 3	Model 4	Model 5
Service robot mention		0.27***	0.36***	0.54***	0.41***	0.37***
		(0.05)	(0.05)	(0.06)	(0.07)	(0.10)
Rapport with robot*	H1	0.49***				0.50***
Service robot mention		(0.08)				(0.08)
Customer review effort focused on the robot*	H2		−0.60*			−0.55*
Service robot mention			(0.23)			(0.24)
Device deployed to post the review*	H3			0.28**		0.32**
Service robot mention				(0.10)		(0.10)
Log (online review experience of the customer)*	H4				0.01	−0.03
Service robot mention					(0.02)	(0.02)
Observed average rating		1.56***	1.56***	1.56***	1.56***	1.56***
		(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
Identity disclosure		−0.004	−0.003	−0.003	−0.003	−0.004
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Log (online review experience of the customer)		−0.04***	−0.04***	−0.04***	−0.04***	−0.04***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Device deployed to post the review		−0.05	−0.09*	−0.05	−0.05	−0.09*
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Traveled on business		−0.49***	−0.50***	−0.50***	−0.50***	−0.49***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Traveled solo		0.10****	0.10****	0.10****	0.10****	0.10****
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Traveled with family		−0.10**	−0.10*	−0.10*	−0.10*	−0.10*
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Traveled with friends		−0.04	−0.04	−0.04	−0.04	−0.04
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Log (review length in number of words)		−0.72***	−0.72***	−0.73***	−0.72***	−0.73***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Further controls						
Year dummies		Included	Included	Included	Included	Included
Chain		Included	Included	Included	Included	Included
Star rating		Included	Included	Included	Included	Included
Hotel ID		Included	Included	Included	Included	Included
Intercept-1		−0.78	−0.77	−0.80	−0.76	−0.81
		(0.84)	(0.84)	(0.84)	(0.84)	(0.84)
Intercept-2		0.01	0.02	−0.001	0.03	−0.02
		(0.84)	(0.84)	(0.84)	(0.84)	(0.84)
Intercept-3		0.93	0.93	0.91	0.94	0.89
		(0.84)	(0.84)	(0.84)	(0.84)	(0.84)

TABLE 4 (Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept-4	2.48**	2.49**	2.47**	2.50**	2.45**
	(0.84)	(0.84)	(0.84)	(0.84)	(0.84)
Observations	20,166	20,166	20,166	20,166	20,166
Pseudo R^2	13.2%	13.1%	13.0%	13.0%	13.3%
Log likelihood	−22,248.6	−22,261.9	−22,263.0	−22,266.2	−22,240.7

Note: Standard errors are in parentheses.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; $^{****}p < 0.1$.

Our study extends previous literature that has focused on tackling the direct effect of service robots on customer satisfaction (e.g., Luo et al., 2021) by exploring moderating effects. Of the moderators, the first relates to the actual service encounter with a service robot, and the other three refer to the process of posting the review.

5.1.1 | Rapport during the service encounter

Our first moderator was rapport between the service robot and the customer during the service encounter. This finding expands our understanding of the role of rapport in service encounters (Gremler & Gwinner, 2000; Seo et al., 2018) and extends it to interactions with service robots. In particular, our study addresses the gap in testing rapport as a moderator of customer satisfaction, as theorized by the sRAM (Wirtz et al., 2018). Furthermore, from a service marketing perspective, the study extends research that has examined how rapport can help improve customer–service provider interactions with both humans (Gremler & Gwinner, 2000) and nonhuman agents (i.e., service robots) (Seo et al., 2018). Previous evidence shows that rapport strategies can increase engagement with the service experience (Tung & Au, 2018), yet our study indicates that it can also have a moderating effect of service robots on customer satisfaction.

5.1.2 | Customer effort focused on the service robot when writing the review

Our second moderator (the first of the remaining moderators that focused on the process of posting the review), examined customer effort focused on service robots in their review (e.g., the proportion of the review relating to a robot). We found that increased focus on the service robot weakened the robot–satisfaction rating relationship.

This finding extends previous eWOM literature assessing the impact of reviewing effort on customer satisfaction (Chevalier & Mayzlin, 2006; Xu & Li, 2016; Zhao et al., 2019) to the evaluation of the service robot–customer satisfaction relationship. Our results suggest that the tendency of posting more detailed comments on the negative attributes of the service consumption extends to the overall evaluation of service robots. Indeed, the more a customer focused on robots in their reviews, the lower was their online rating.

5.1.3 | Device deployed to post the review

Our third moderator—the device customers deployed to post the review—found that using a mobile device (vs. a nonmobile device) had a positive impact on the robot-satisfaction ratings relationship. We propose that the use of a mobile device functions as a proxy for high levels of immediacy between the service encounter and the writing and posting of a review. Therefore, our findings suggest that when customers share their experience of their robot service encounter in temporal proximity (i.e., relatively close in time after a service encounter happened), the service robot-satisfaction online rating relationship is strengthened.

This finding further extends previous conceptualizations of the role of temporal distance and the immediacy between service encounter with a service robot and the assessment of that interaction. Research has found that, postexperience, the immediacy in which consumers recollect the service encounter can amplify the effect (positively or negatively) of that interaction (Melumad et al., 2019; Ransbotham et al., 2019). This moderating effect was also found in the context of interactions with service robots, extending the principles of CLT (Trope & Liberman, 2003) that high temporal immediacy with a focal object will lead to a focus on more concrete aspects of that interaction. In the case of service robots, this can also relate to service quality attributes, as found in previous research (Luo et al., 2021).

Furthermore, this finding adds to existing knowledge around the generation of eWOM in the context of service robotics. Previous research has found that reviews submitted via mobile devices tend to be more extreme in valence, that is, more positive or negative (Mariani et al., 2019).

5.1.4 | Customer's prior online review experience

The final moderator relates to the customer's prior experience in writing online reviews (i.e., the number of past reviews posted). We found it to be unrelated to the service robot–satisfaction rating relationship. Online review experience with different services, which might make customers more inquisitive and demanding, did not moderate the relationship between the presence of a service robot and how satisfied the customer was with the experience.

Unobserved familiarity with service robots may explain this outcome. Specifically, it is possible that online review experience is unconnected to how familiar customers are with service robots. Perhaps, only customers with sufficient prior knowledge about robots are able to appreciate the robot–satisfaction relationship. Moreover, since service robots were not a standard service attribute, experienced online reviewers were not necessarily more familiar with service robots (a novice reviewer might have stayed at a hotel and posted a review only because of the robot). Thus, how familiar customers are with robots (an indicator that we are not able to capture with our data) might be a factor explaining the null effect for our fourth moderator.

5.2 | Managerial implications

This study has several implications for hotel management. First, our findings provide further support for the service robot–customer satisfaction main effect (Borghi & Mariani, 2021; Luo et al., 2021; Tung & Au, 2018). This suggests that service robots should continue to be deployed in customer-facing service processes as they generally improve customer satisfaction.

Second, our study emphasizes the importance of designing service robots—their interaction capabilities and behaviors—so that customers can build rapport with them. For example, creating conversational flows that are more personal in nature, demonstrating aspects of the robot's personality, and asking for specifical feedback on an interaction by calling the robot by its name. The latter should be visible and easy to remember to increase guest' likelihood to recall it. For instance, the most frequently mentioned names in our sample are short (e.g., Leo and Cleo).

Third, our findings suggest the importance of encouraging and nudging guests to use their mobile devices to provide timely feedback on their positive service experiences. This might include marketing-specific tools that help manage customer relationships (e.g., text messaging via customer CRM systems with requests for posting a review) or offering "Instagrammable" cues (e.g., let the service robot ask whether the customer wants to take a photo with it), and other social media prompts (e.g., "We would be grateful for your review on TripAdvisor"). Service providers should also formulate and implement offline response management strategies to address dissatisfied customers and their complaints. They should encourage customers to use oral communication, text messaging and emails rather than online reviews to express their unhappiness (e.g., "if you are happy tell your friends, if not, tell us").

Fourth, this study reveals that higher customer effort focused on service robots in a review reduces the service robot–satisfaction rating relationship. The tendency of posting more detailed comments on the negative aspects of human–robot interactions may contribute to discourage future travelers from interacting with service robots. Consequently, to circumvent service robots' failures, we recommend that hotel managers implement specific monitoring and recovery mechanisms. For instance, operations managers should utilize a dedicated dashboard equipped with performance indicators relevant to service robots. Such an approach enables real-time assessment of robot performance and facilitates prompt action in case of failure. Particularly, given the widespread adoption of delivery robots, hotel operations managers should closely monitor delivery timings and establish predetermined minimum performance thresholds in terms of timing. When these thresholds are not met, it is advisable for a human employee to intervene and address the situation. This proactive measure stems from our analysis of human-robot interactions within the data set, where software issues occasionally led to instances of incorrect room deliveries or robots becoming trapped in elevators.

5.3 | Limitations and further research

Our study has a few limitations that offer avenues for further research. First, we explored four moderators of the service robot–customer satisfaction relationship and future research could examine additional potential moderators. For instance, it would be interesting to explore whether characteristics of the robot (e.g., level of anthropomorphism, perceived warmth, and gender) are potential moderators. The role of robot characteristics in human–robot interactions has been the object of marketing studies (e.g., Blut et al., 2021; Seo, 2022), therefore, it would be valuable to test, empirically, if characteristics act as moderators of the relationship between the deployment of robots and customer satisfaction online ratings.

Second, recent research suggests that in addition to being a moderator, rapport could also be a mediator of the robot-satisfaction link (e.g., Blut et al., 2021). Further research could examine recurrent interactions between the same customer and a robot over extended periods to establish whether rapport would be established over time and then mediate the robots-satisfaction link.

Third, our study only captures the views of those customers who wrote and posted online reviews, which might lead to overrepresenting the views of customers with highly positive and negative experiences. Customers with experiences that do not stand out, or customers who do not write reviews, were not represented in our sample. We suggest that other methods, such as intercept surveys, might be deployed to capture customers with the full range of service experiences.

Fourth, we confined our study to a sample of service encounters in hospitality. To enhance the generalizability of our findings, the model might be tested in other industries such as healthcare (Belanche et al., 2020), legal (Harashima, 2019), and financial services (Wirtz et al., 2023), where service robots are increasingly being adopted.

Finally, further research could explore customers' sociodemographic characteristics as controls in the econometric models. Since sociodemographic indicators are not mandatory features in TripAdvisor profiles, they are disclosed only by a very small number of users. Due to the high proportion of missing values for these variables in our data set, we could not take them into account in our empirical analysis.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Research data are not shared.

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