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Human Versus Robot: Comparing Service Agents in Hospitality Settings—Insights From a Field Study

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ABSTRACT

The hospitality industry is facing personnel challenges, including personnel shortages and high staff turnover, asking practitioners to explore service robots to enhance competitiveness. While prior academic studies have primarily relied on hypothetical or conceptual research, there remains a pressing need for real-life field studies to assess the practical impacts of service robots in hospitality. This study examines the comparative effects of human and robotic service agents at the touchpoint of information provision in a real-world hotel setting. Using a field experiment with 200 participants, where both service agents (human and robot) were simultaneously available, we assess service agent's impact on guests' experience of hospitality, satisfaction, and revisiting intentions. The findings reveal indifferent effects between human and robotic agents, challenging assumptions that robots negatively impact guest experiences. Contrary to debates suggesting that human agents are superior in hospitality roles, our results indicate that service robots can effectively complement human staff, reducing demand for frontline personnel and lowering operational costs without diminishing guest satisfaction. This study highlights the potential of integrating robotic agents into the hospitality frontline, particularly for routine tasks like information provision. We acknowledge limitations, including the focus on a single touchpoint, and call for broader research across diverse guest interactions and touchpoints. Future studies should also explore the underlying factors influencing guests' choice of service agents. These findings offer practical implications for tackling labor shortages while maintaining service quality, providing actionable insights for the hospitality industry in the context of digital transformation.

1 | Introduction

Service robots—system-based autonomous and adaptable interfaces for customer interaction and service delivery—are increasingly used in hospitality to address staff shortages and enhance guest experiences (Kim, So, and Wirtz 2022; Pitardi et al. 2022; Van Doorn et al. 2023; Wirtz et al. 2018). Distinct from static technologies like self-service kiosks, human-like service robots introduce a social dimension to guest interactions, enabling more dynamic and engaging encounters (Tuomi, Tussyadiah, and Hanna 2021). This surge in hospitality robots offers solutions to labor shortages, with 97% of US hotels reporting such issues (AHLA 2022). Recent studies have explored guest reactions to robots through hypothetical scenarios and reviews (Belanche, Casaló, and Flavián 2021; Choi et al. 2020; Hoang and Tran 2022) or movie clips (Kim and So 2022), revealing mixed perceptions of robots' capabilities in hospitality roles. Results of these studies either point out that guests deem humans better at hospitality tasks than robots (Choi et al. 2020; Hoang and Tran 2022) or shed light on the relationships between robot attributes (such as human-likeness and social presence) and usage intentions

Summary

- The field study compares human and robotic service agents in a hospitality context, specifically for providing information to guests.
- Results indicate that both robotic and human service agents had similar effects on guests' satisfaction and their touchpoint revisit intention.
- Contrary to common concerns, robotic agents did not negatively affect the experience of hospitality and could help alleviate personnel shortages.
- The study highlights the need for further research on different types of guest interactions with service robots across various touchpoints.
- Practical implications suggest that integrating robotic agents like concierge robots could be beneficial in managing current staffing challenges without compromising service quality.

(Belanche, Casaló, and Flavián 2021; Huang et al. 2021; Kim and So 2022; Ozturk et al. 2023). Debates around human–robot–guest interactions shed light on potential cost efficiencies and service productivity gains through service robots as (partial) service providers (Grönroos and Ojasalo 2004; Kim and So 2022; Odekerken-Schröder et al. 2022). The debates intersect with discussions on digital transformation in hospitality, which emphasize the need to align technological advancements with operational efficiencies and guest-centric service strategies (Busulwa 2022). Similarly, Belanche, Casaló, and Flavián (2021) argue that service robots can achieve efficiency gains while maintaining competitive service quality, particularly when human and robotic agents are integrated effectively.

Since latest contributions are skewed towards studies on *usage intention* (Huang et al. 2023; Kim, So, and Wirtz 2022), there is a need for real-life studies in which guests actually interact with robots. Thus, we ask the following: *What is the impact of implementing service robots as service agents (alongside humans as service agents) on the guests' hospitality experience, satisfaction, and revisit intention?*

This research assesses the impact of service robots alongside human agents on guest satisfaction and revisit intentions in a hotel context. We contribute to debates on digitalization in hospitality, guest experience with technology, and the emotional responses to robotic service encounters, offering insights into the integration of robots at guest touchpoints and the effect on competitiveness (Tung and Law 2017).

Our findings provide empirical evidence on the effectiveness of service robots in hospitality, challenging assumptions about their (negative) impact on the guest experience and suggesting practical implications for managing staff shortages, improving service delivery and competitiveness. This study enriches the discussion on human–robot interactions in hotels by exploring how these interactions influence guest satisfaction and the likelihood of revisiting (Tussyadiah, Zach, and Wang 2020; Yoganathan et al. 2021).

2 | Literature Background and Hypotheses Development

2.1 | Service Robots in the Hospitality Service Frontline

We view service robots as "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organisation's customers" (Wirtz et al. 2018, 4). Unlike established digital technologies, such as self-service kiosks (often found in airports, restaurants, or hotel lobbies), service robots can take over tasks traditionally performed by humans at the frontline. While static self-service technologies are typically limited to functional tasks and lack the capability to empathize or engage with guests on a social level (Brengman et al. 2021). Researchers highlight a critical gap in understanding the *real-life* interactions between humans and service robots, which are considerably more dynamic and socially complex in their interactions with humans (Yoganathan et al. 2021).

Service robots can potentially entail more human-like (i.e., anthropomorphic) characteristics, that can significantly influence customer attitudes, expectations, and experiences at the frontline (Blut et al. 2021; Tuomi, Tussyadiah, and Hanna 2021). Anthropomorphism refers to the attribution of human-like qualities to nonhuman entities, often through design elements or interaction styles. For service robots, anthropomorphism may involve physical features such as shape, expressions, or visual cues, as well as interaction characteristics, like natural language use, gestures, and other nonverbal cues (Murphy, Gandudi, and Adams 2020). These human-like features enable service robots to embody a social dimension, differentiating their interactions from traditional, static technologies like kiosks (Tuomi, Tussyadiah, and Hanna 2021). This distinct ability underscores the transformative potential of service robots in hospitality settings, where personalized and engaging interactions are crucial to enhancing guest experiences (Pijls et al. 2017).

Scholarly debates emerged to capture the specificities of service robots in the frontline and their effects in hospitality settings. Table 1 illustrates the related work of service robots, hospitality settings, and guest experience.

Mende et al. (2019, 535) frame service robots as "the most dramatic evolution in the service realm." While studies have begun to explore how service robots are changing the way guests interact with service providers (Mende et al. 2019), the impact of guests' interaction with service robots on the overall customer service experience and robot reuse intentions are still largely under-researched.

Through their anthropomorphic and social characteristics, service robots are (to a certain extent) capable of showing empathetic behavior, which is a core element of providing positive experiences in hospitality settings. Tuomi, Tussyadiah, and Stienmetz (2021) found that some participants interacting with a humanoid robot in a restaurant setting saw the robot as a "member of staff" rather than a tool and referred to the robot by personal pronouns (he/she). Service robots are social entities that

TABLE 1 | Related work at the intersection of service robots, hospitality, and guest experience.

Authors	Method	Research context	Measurement constructs	Key findings
Brengman et al. (2021)	Field experiment, comparison between robot and tablet interface	Retail store	Interaction time, number of interactions, amount of money spent	Humanoid service robots elicited greater interactions than the tablet kiosks in the frequency and duration of interaction with consumers. Further, the robots increased in-store traffic and consumer attraction and resulted in higher sales than tablet kiosks.
Chi, Gursoy, and Chi (2022)	Structural equation modelling	Hotels and airport service settingsl	Perceived social influence, hedonic motivation, anthropomorphism, perceived performance expectancy, perceived effort expectancy, emotion, willingness to use AI devices, objection to the use of AI devices	Tourists' acceptance of AI devices is influenced by social influence, hedonic motivation, anthropomorphism, performance expectancy, effort expectancy, and emotions towards the devices.
De Kervenoael et al. (2020)	Structural equation modelling and interviews	Restaurants and hotels	Perceived usefulness, perceived ease of use, service assurance, personal engagement, tangibles, empathy, perceived value, information sharing, intention to use a social chatbot	Visitors' intentions to use social robots stem from the effects of technology acceptance variables, service quality dimensions leading to perceived value, and two further dimensions of human-robot interaction (HRI): empathy and information sharing.
Kim, So, and Wirtz (2022)	Structural equation modelling	Hotels	Perceived intelligence, perceived social presence, perceived social interactivity, rapport, trust, uniqueness neglect, usage intentions	Perceived intelligence perceived social presence and perceived social interactivity affect trust and usage intentions. Perceived intelligence, perceived social presence and perceived social interactivity affect rapport and usage intentions.
Lu, Cai, and Gursoy (2019)	Exploratory factor analysis	Hotels	Performance efficacy, intrinsic motivation, anthropomorphism, social influence, facilitating conditions, emotions	Hospitality customers' intentions to use AI devices are affected by social influence, hedonic motivation, anthropomorphism, performance and effort expectancy, and emotions.
Odekerken-Schröder et al. (2022)	Field experiment, structural equation modeling	Restaurant	Anthropomorphism, social presence, service triad, customer repatronage, hedonic value, utilitarian value	Anthropomorphism is associated with social presence; utilitarian value is associated with customer repatronage.
Qiu et al. (2020)	Structural equation modelling	Hotels	Service robot attributes, rapport building between customer and service robot, rapport building between customer and employee, hospitality experience	Robots' being perceived as human-like or intelligent positively affects customer-robot rapport building and the hospitality experience. Customer–employee rapport building mediates the relationship between robot attributes and the hospitality experience, which customer–robot rapport building does not.

(Continues)

TABLE 1 | (Continued)

Authors	Method	Research context	Measurement constructs	Key findings
Song and Kim (2022)	Interviews, video clip stimuli, empirical data collection	Fashion, technology, food service	Usefulness, social capability, appearance, attitudes toward human robot interaction, service quality, robot acceptance	Robots' usefulness, social capability, and appearance influence attitudes toward robot interaction positively, which in turn, predicts anticipation of better service quality and greater acceptance of robots.
Tussyadiah and Park (2018)	Structural equation modeling, biometric measurements	Tourism and hotel operations	Anthropomorphism, animacy, likeability, perceived intelligence, perceived security, adoption intention, importance of operations	Consumers' intention to adopt hotel service robots is influenced by human–robot interaction dimensions of anthropomorphism, perceived intelligence, and perceived security.

exhibit both human- and nonhuman characteristics through social presence, ultimately affecting the guests' experience.

Guests' attitudes toward robotic service agents have become a popular research topic. Recent studies discuss users' intentions to use robots. For instance, Chi, Gursoy, and Chi (2022) found that guests' acceptance of robots is influenced by social influence, hedonic motivation, anthropomorphism, performance expectancy, effort expectancy, and emotions toward the devices. Tussyadiah and Park (2018) found that consumer intention to adopt hotel service robots is influenced by human–robot interaction dimensions of anthropomorphism, perceived intelligence, and perceived security.

Linking to the ongoing academic debate, we compare human and robotic service agents and their effect on previously established relationships between social presence, experience of hospitality, familiarity with service robots, guest satisfaction with touchpoint experiences, and touchpoint revisit intention.

2.2 | Social Presence as a Precondition for Shaping Guest Experience and Satisfaction With Service Robots in Hospitality

We understand social presence as the degree of mediated communication or social ambience within a social environment. Social presence captures the perception that makes consumers feel they are in another social entity's company and is conceptualized as a decisive antecedent for customer experience (Kim and So 2022). We refer to recent studies showing a positive relation to guest satisfaction in the hospitality industry: Higher degrees of perceived social presence in a service encounter have been found to enhance guest experience, thereby leading to competitiveness outcomes such as customer satisfaction and loyalty (Yoganathan et al. 2021). Consequently, previous empirical research on service robots argues for social presence as a significant predictor of guest satisfaction and other positive behavioral intentions, such as revisiting intentions, in hospitality contexts (Odekerken-Schröder et al. 2022).

Social presence can influence guests' perceived experience within a hospitality context, which ultimately is a key determinant of their satisfaction of a service encounter. Due to their unique anthropomorphic characteristics, service robots can be perceived as having social presence. We hypothesize the following:

H1. *Perceived social presence of a service agent (human or robotic) is positively associated with perceived hospitality experience.*

H1a. *When interacting with a human service agent (vs. robotic service agent), guests perceive a higher degree of social presence, leading to a higher degree of perceived hospitality experience.*

H2. *Perceived social presence of a service agent (human or robotic) is positively associated with satisfaction of a touchpoint.*

H2a. *When interacting with a human service agent (vs. robotic service agent), guests perceive a higher degree of social presence, leading to a higher degree of satisfaction.*

2.3 | Hospitality Experience as a Necessary Condition for Guest Satisfaction in a Hospitality Setting

We follow Becker and Jaakkola and view customer experience as "non-deliberate, spontaneous responses and reactions to particular stimuli" (2020, 637). In the existing customer experience literature, there is a broad consensus that experience is a key driver for guest satisfaction and favorable guest behavior, ultimately determining business competitiveness (e.g., loyalty, increased sales, or bookings) (Kim and So 2022; Pizam et al. 2022). Given the relevance of experiential factors in hospitality, Pijls et al. conceptualized the 'experience of hospitality' measure as "the [guest's] experience of staff behaviour as well as the experience of the physical service environment including its facilities" (Pijls et al. 2017, 126). This framework highlights three dimensions of hospitality: inviting (the extent to which the organization creates an open, welcoming atmosphere), care (the degree to which the organization demonstrates attentiveness and personal engagement), and comfort (the level of ease and relaxation experienced by guests), which together form a comprehensive measure of how guests perceive and evaluate the hospitality offered.

Building on the notion that various stimuli influence experience, we view the respective service agent (human vs. robotic) at a specific touchpoint as a stimulus which is controlled by the firm (human: through standard operating procedures, robot: through programmatic configuration) (Becker and Jaakkola 2020). In hospitality settings, Qiu et al. (2020) found that robots, which are perceived as human-like or intelligent, positively affect customer–robot rapport building, which in turn positively influences the guest's hospitality experience.

A recent systematic review by Hollebeek et al. (2024) highlights that customer experience is inherently tied to customer satisfaction through its role in shaping emotional and behavioral responses to service encounters. Linking to Pijls et al. (2017), we conceptualize the "experience of hospitality" as a specific notion of customer experience, emphasizing its positive impact on guest satisfaction.

Finally, we link to Wirtz et al. (2018), who identify *social presence* as a critical factor for the acceptance of service robots, framing it as a key social–emotional antecedent of guest satisfaction. Wirtz et al. further argue that experience factors, such as a guest's experience of hospitality, directly influence satisfaction, underlining their central role in shaping favorable outcomes. Therefore, we assume an indirect positive relationship between social presence and guest satisfaction via experience of hospitality:

H3. *Perceived hospitality experience is positively associated with satisfaction of a touchpoint.*

H3a. *When interacting with a human service agent (vs. robotic service agent), guests perceive a higher degree of hospitality experience, leading to a higher degree of satisfaction.*

H4. *Perceived social presence is positively associated with satisfaction of a touchpoint via the perceived hospitality experience of that touchpoint.*

2.4 | Familiarity With Service Robots as Favorable Condition for Guests' Satisfaction

Linking to earlier studies discussing influential factors on customer experience (Becker and Jaakkola 2020; Heinonen et al. 2010; Jüttner et al. 2013), we understand customers' familiarity with service robots as a relevant factor affecting perceived hospitality experience and the evaluative outcome of touchpoint interactions. Familiarity with service robots consists of experiential and perceptual familiarity.

First, *experiential familiarity relates to* guests' prior interactions with robots, shaping their comfort and ease in engaging with these technologies. Guests who have had frequent exposure to robots, for example, may feel more comfortable interacting with them and perceive their presence more positively (Lu, Cai, and Gursoy 2019; Seo 2022). Second, *perceptual familiarity*—or anthropomorphic familiarity—relates to the robot's human-like appearance and behavior. Service robots equipped with anthropomorphic features, such as gestures, facial expressions, or natural language capabilities, can foster a sense of familiarity even for guests with limited prior exposure, as these characteristics align with human schemas and encourage social engagement (Belanche, Casaló, and Flavián 2021; Tuomi, Tussyadiah, and Stienmetz 2021). Research has shown that service robots with human-like characteristics may help reduce feelings of social judgment, as they appear more like a "member of staff" than a tool, potentially increasing comfort during the interaction (Tuomi, Tussyadiah, and Stienmetz 2021).

We hypothesize that guests' familiarity with service robots—whether from direct experience or from the robot's human-like features—in hotel settings is a decisive contingent factor, augmenting the positive associations with guest satisfaction and hospitality experience:

H5. *Guests' familiarity with service robots moderates the relationship between experience of hospitality and guest satisfaction, such that this relationship is stronger when guests report greater familiarity with service robots, regardless of the type of service agent (human vs. robot).*

2.5 | Guest Satisfaction as a Favorable Precondition for Guests' Intentions to Revisit Touchpoint

Guest satisfaction is decisive in determining a guest's likelihood to revisit or recommend a hospitality touchpoint, making satisfaction a crucial factor for business competitiveness.

Behavioral intention refers to a guest's intention to behave in a particular manner, for example, returning to a hotel or recommending an experience to others. Guan et al. (2022) confirm the positive association between satisfaction with service robots in restaurant settings and desired behavioral intention. Truong et al. (2020) conceptualized the positive relationships between technological innovations applied in the service frontline and resulting positive competitiveness effects, such as guest satisfaction and desired behavioral intention (e.g., word-of-mouth recommendations, re-purchase intention).

H6. *Regardless of the type of service agent (robotic vs. human), guest satisfaction with a touchpoint is positively associated with the intention to revisit this touchpoint.*

2.6 | Theoretical Model

We follow Kim, So, and Wirtz (2022) and integrate our main hypotheses in one conceptual model (Figure 1), which guides both scenarios of our study. Since we aim to compare human and robotic service agents, we build on this conceptual model for developing and testing both scenarios (human vs. robotic service agent) independently, before comparing the cross-scenario effects.

Table 2 provides an overview of the variables used in this study.

3 | Methodology

3.1 | Real-Life Field Study Set Up

Given that the study aims to evaluate the comparative effects of human and robotic agents at touchpoints, a field study in a real-world hospitality setting (here: reception area) is well-suited to provide insights into guests' perceptions and behavioral intentions, while enhancing the ecological validity of our study (Viglia and Dolnicar 2020).

We set up a service robot (i.e., hotel concierge robot, see Figure 2) in a real-life reception area. The reception area is in a hospitality venue on a university campus in the Netherlands, connected to a 24-bedroom hotel. The hotel is 3-star categorized, with an average daily rate of 140 Euros, hosting both business and leisure guests. The robot that was used is an out-of-the box concierge robot. This robot can take over tasks of information provision in hotels. We designed two alternative scenarios for guests to experience the specific touchpoint of *information provision*: (1) interacting with a human frontline employee, or (2) interacting with the concierge robot.

3.1.1 | Scenario 1: Guest Interacts With Frontline Reception Employee

Guests interacted with the regular front office employee for information services. These employees, informed about the study, adhered to standard operating procedures during interactions, such as guiding guests to specific areas or recommending restaurants from a pre-selected list, ensuring consistent service across different staff members at reception touchpoints. The standard operating procedures ensure high consistency across involved human frontline employees.

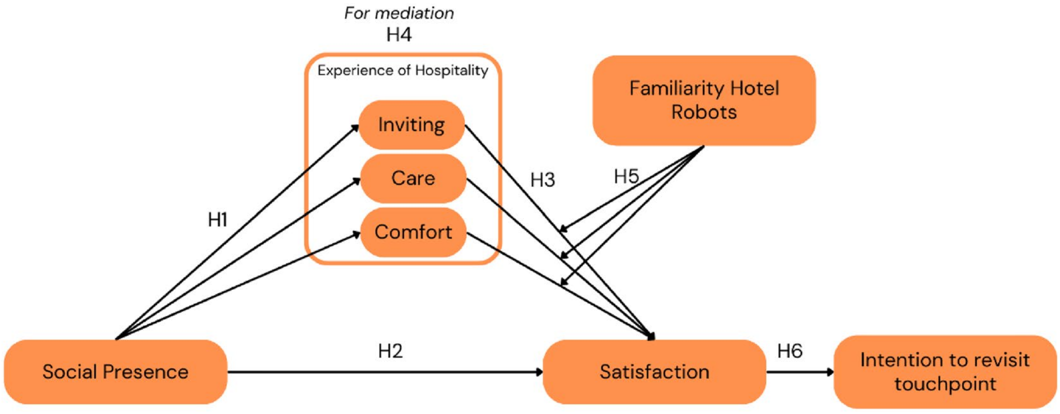

FIGURE 1 | Underlying conceptual model for both scenarios (human vs. robotic service agent). [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 2 | Overview of variables.

Type of variable	Variable description	Key references
Experimental variable	Type of service agent (human, robot)	—
Independent variables	Social presence	Kim, So, and Wirtz (2022); Yoganathan et al. (2021)
	Hospitality experience	Pijls et al. (2017)
	Guest satisfaction	Guan et al. (2022); Truong et al. (2020)
Moderating variable	Familiarity with service robots	Lu, Cai, and Gursoy (2019); Seo (2022)
Dependent variable	Touchpoint revisiting intention	Pijls et al. (2017); Shin, Fan, and Lehto (2021)

FIGURE 2 | TEMI concierge robot. [Color figure can be viewed at wileyonlinelibrary.com]

3.1.2 | Scenario 2: Guest Interacts With Concierge Robot

Guests interacted with Temi, a concierge robot equipped with personal assistant functionalities, capable of performing tasks like a hotel receptionist, like providing directions and information about the hotel and area. Temi operates autonomously on wheels and uses a tablet for communication, also supporting spoken language interaction. Developed with a robotic programming company, Temi was stationed in the reception area, offering guests the choice to interact with it or human staff. Besides offering auditory and visual guidance, Temi could navigate guests to various hotel locations. The robot was placed prominently in the reception area, accompanied by an information banner suggesting an alternative interaction touchpoint to the frontline employees.

3.1.3 | Data Collection

We conducted a quantitative online survey, validated and refined by five hospitality researchers and three service robot experts. Data were collected over 3 weeks, with surveys administered daily from 9 a.m. to 5 p.m. A team of two incognito researchers at the venue invited guests to participate in the survey after they interacted with either human staff or the concierge robot, ensuring unbiased real-world conditions. The approach was uniform across various times of day, without influencing guests' interaction choices.

3.2 | Sample

Our study sampled 200 guests from a hospitality venue, who interacted with either a frontline employee or a concierge robot for information provision (Table 3). After removing one response for insufficient engagement, our valid sample comprised 101 participants in the human–human interaction group and 99 in the human–robot interaction group. The average participant age across both groups was 25 years, which reflects the demographic composition of the venue's guest population. We found no issues with response validity, such as outliers or suspicious patterns.

3.3 | Measured Constructs

We used validated measures, which have been empirically tested in previous studies. For consistency reasons, we adapted the scale format of all measures to a 7-point Likert scale (1 = *totally disagree*, 7 = *totally agree*), if not indicated differently. The exact phrasing of the questions can be found in Table 4.

To measure the independent variable *perceived social presence* of technological innovations, we built on items from the scale by Gefen and Straub (1997, 2004). We adapted Pijls et al.'s (2017) scale to operationalize the mediating variable of *perceived experience of hospitality* of a touchpoint. We included a measure to capture participants' *familiarity with hospitality service robots* to operationalize the moderating effect in our model. To measure dependent variables of competitiveness, we built on items proposed by (a) Angelova and Zekiri (2011) to capture *guests' satisfaction* with the touchpoint interaction, and (b) Pullman and Gross (2004) to capture *guests' intention to revisit the touchpoint*.

4 | Results

4.1 | Preliminary Data Analysis

We follow earlier studies in hospitality and tourism (e.g., Kim, So, and Wirtz 2022), and tested the theoretical model with partial least squares structural equation modelling (PLS-SEM) with the SmartPLS 4 software (Sarstedt et al. 2020). Preliminary analyses were conducted to evaluate data heteroscedasticity, independence, linearity, and normality (Tabachnick and Fidell 2019). We further conducted a full collinearity test by simultaneously evaluating lateral and vertical collinearity (Kock 2015). VIF values were calculated to assess multicollinearity. As shown in Table 4, the values were less than 5, which suggests multicollinearity was not an issue (Avkiran and Ringle 2018). Also, skewness and kurtosis did not exceed 2, suggesting a normal data distribution (Hair et al. 2017). We used G*POWER 3.1 software to test for statistical power. Our sample size of $N = 99$ and $N = 101$ for an error likelihood of 0.05 and medium effect size of 0.5 gave a statistical power of 0.89, which lies above the cutoff of 0.80 (Faul et al. 2009).

TABLE 3 | Demographics.

Age		Gender		Service agent	
Under 18	7	Female	109	Human	99
18–25	136	Male	85	Robot	101
25–34	38	Other	4		
35–44	11	Prefer not to say	2		
45–54	6				
55–64	2				

4.2 | Measurement Model

To guarantee sufficient construct reliability, we looked at standard loadings, average variance extracted (AVE), Cronbach alpha and Dijkstra–Henseler's rho (pA), displayed in Table 4. All standard loadings exceed the 0.7 thresholds (Hair et al. 2017). AVE values for each construct are above the 0.5 thresholds (Fornell and Larcker 1981). The rho-a and Cronbach alpha values are also above the 0.7 thresholds, showing good reliability (Hair et al. 2017).

4.3 | Discriminant Validity

We conducted two tests to check discriminant validity. First, we investigated the cross-loadings of the indicator items, and no considerable cross-loadings were observed. Second, we adopted the Fornell Larcker test, where the square root of the AVE for each construct is compared to the inter-construct correlations for each construct (Fornell and Larcker 1981). The square root of the AVE for each construct was higher than the inner construct correlations. Thus, discriminant validity was satisfied. Results of the Fornell Larcker tests are displayed in Table 5.

4.4 | Structural Model and Hypothesis Testing

In line with our research question, we compare two scenarios, that is, guests' interaction with a human versus robotic service agent for the touchpoint of information provision (see Figure 3). In line with existing research, we analyze the effect of the binary variable (human vs. robotic service agent) subsequent to a separate analysis of the structural models of the two scenarios (Sarstedt et al. 2022).

4.4.1 | Scenario 1: Human–Human Interaction

Table 6 shows the difference path coefficients and p values for each path as well as the f-square values and 95% confidence intervals for the human–human case. To evaluate model fit, we use Standardized Root Mean Square residual (SRMS), which should remain under 0.08 for a good model fit (Henseler, Ringle, and Sarstedt 2016; Hu and Bentler 1998). With SRMS values of 0.051, this condition is satisfied. We also evaluated the model's predictive power by estimating the R^2 values, which were all above 0.10 (Falk and Miller 1992).

As Table 6 shows, social presence was significant in determining the experience of hospitality (H1) in terms of inviting ($\beta=0.785$, $p<0.001$), care ($\beta=0.838$, $p<0.001$), and comfort ($\beta=0.739$, $p<0.001$). Social presence was also significant in determining satisfaction (H2: $\beta=0.248$, $p=0.05$). Experience of hospitality was insignificant for determining satisfaction for the aspect of inviting (H3: $p>0.05$) and significant for care (H3: $\beta=0.241$, $p=0.05$) and comfort (H3: $\beta=0.347$, $p<0.001$). Familiarity with hotel robots moderates the relationship between the experience of hospitality and satisfaction insignificantly for the aspects of inviting (H5: $p>0.05$) and comfort (H5: $p>0.05$) and negatively for the aspect of care (H5: $\beta=-0.283$, $p=0.014$). Satisfaction is significantly associated with touchpoint revisit intention (H6: $\beta=0.868$, $p<0.001$).

We further assessed the mediating effects of social presence on satisfaction via experience of hospitality. The path coefficients are displayed in Table 6 and show that the effect of social presence on satisfaction is partially mediated by the experience of hospitality via the aspects of care (H4: $\beta=0.202$, $p=0.049$) and comfort (H4: $\beta=0.256$, $p<0.001$) and not via inviting (H4: $p>0.05$).

4.4.2 | Scenario 2: Human–Robot Interaction

Table 6 further shows the difference path coefficients and p values for each path as well as the f-square values and 95% confidence intervals for the human–robot case. The SRMS value is 0.064, demonstrating a good model fit (Henseler, Ringle, and Sarstedt 2016; Hu and Bentler 1998). R^2 values were also all above 0.10 (Falk and Miller 1992).

As Table 6 shows, social presence was significant in determining the experience of hospitality (H1) in terms of inviting ($\beta=0.710$, $p<0.001$), care ($\beta=0.714$, $p<0.001$), and comfort ($\beta=0.604$, $p<0.001$). Social presence was also significant in determining satisfaction (H2: $\beta=0.297$, $p=0.001$). Experience of hospitality was significant in determining satisfaction for the aspect of inviting (H3: $\beta=0.230$ $p=0.03$), care (H3: $\beta=0.236$, $p=0.037$), and comfort (H3: $\beta=0.226$, $p=0.009$). Familiarity with hotel robots does not moderate the relationship between the experience of hospitality and satisfaction for the aspects of inviting (H5: $p>0.05$), care (H5: $p>0.05$) and comfort (H5: $p>0.05$). Satisfaction is significantly associated with behavioural intention (H6: $\beta=0.873$, $p<0.001$).

We further assessed mediating effects of social presence on satisfaction via experience of hospitality (see Table 7). The path coefficients show that the effect of social presence on satisfaction is partially mediated by the experience of hospitality via the aspects of inviting (H4: $\beta=0.163$, $p=0.037$), care (H4: $\beta=0.168$, $p=0.034$), and comfort (H4: $\beta=0.137$, $p<0.014$).

4.5 | Multi-Group Analysis

We follow existing research, where the majority of Smart PLS studies performs multi group analyses to analyze the effect of binary experimental variables (Sarstedt et al. 2022). We conducted a multi-group analysis to evaluate differences in the path coefficients between the human–human and robot–human groups. We refer to the three-step measurement invariance of composite

TABLE 4 | Construct reliability.

	Human–human interaction								Human–robot interaction							
	Standard Loading	Mean	SD	Skewness	Kurtosis	Cronbach Alpha	Rho a	AVE	Standard Loading	Mean	SD	Skewness	Kurtosis	Cronbach Alpha	Rho a	AVE
Social presence						0.933	0.934	0.79						0.938	0.939	0.801
I experienced a sense of social contact during the interaction	0.888	5.257	1.14	1.662	−0.808				0.866	4.05	1.652	−0.733	0.041			
I experienced a sense of personalness during the interaction	0.902	5.327	1.135	1.541	−0.88				0.879	4.163	1.525	−0.805	0.077			
I experienced a sense of warmth during the interaction	0.911	5.11	1.176	0.767	−0.551				0.887	4.176	1.647	−0.587	−0.208			
I experienced a sense of sensitivity during the interaction	0.857	5	1.152	0.965	−0.474				0.905	3.967	1.493	−0.278	0.095			
Satisfaction						0.93	0.931	0.878						0.875	0.88	0.801
What is your overall satisfaction with the interaction?	0.923	5.178	1.164	0.454	−0.279				0.918	4.96	1.462	−1.104	−0.144			
To what extent has the interaction met your expectations?	0.944	5.29	1.18	0.628	−0.586				0.867	5.066	1.413	−0.748	−0.293			
How close was the interaction compared to the ideal interaction?	0.943	5.089	1.259	0.438	−0.563				0.899	4.297	1.513	−0.718	−0.121			
Revisiting intention						0.908	0.91	0.915						0.861	0.861	0.878
I would choose for this interaction again	0.959	5.069	1.344	0.581	−0.575				0.937	4.68	1.69	−0.619	−0.392			
I would recommend the interaction to others	0.954	5.17	1.313	0.398	−0.534				0.937	4.885	1.513	−0.723	−0.255			
Inviting						0.885	0.885	0.813						0.822	0.842	0.737
The hotel felt inviting during the interaction with Temi/receptionist	0.904	5	1.099	0.775	−0.136				0.869	4.82	1.479	−0.054	−0.456			
I experienced openness during the interaction	0.906	5.178	1.138	0.301	−0.399				0.911	4.776	1.314	−0.663	0.062			

(Continues)

TABLE 4 | (Continued)

	Human–human interaction								Human–robot interaction							
	Standard Loading	Mean	SD	Skewness	Kurtosis	Cronbach Alpha	Rho a	AVE	Standard Loading	Mean	SD	Skewness	Kurtosis	Cronbach Alpha	Rho a	AVE
I experienced freedom during the interaction	0.895	5.283	1.267	−0.402	−0.464				0.79	4.753	1.264	0.026	−0.228			
Care						0.899	0.902	0.714						0.838	0.839	0.756
I experienced support during the interaction	0.881	5.089	1.187	0.295	−0.283				0.809	4.848	1.417	−0.121	−0.476			
I experienced involvement during the interaction	0.9	5.188	1.096	1.124	−0.429				0.86	4.905	1.25	−0.421	−0.128			
The Temi robot/reception employee did its best to take care of me	0.772	5.257	1.24	1.194	−0.726				0.78	5.147	1.414	−0.375	−0.398			
The Temi robot/reception employee relieves me of tasks or worries	0.861	5.16	1.264	1.082	−0.726				0.839	4.305	1.357	−0.397	0.08			
The Temi robotreception employee is interested in me	0.805	5.03	1.198	0.606	−0.549				0.879	4.667	1.525	−0.769	−0.22			
Comfort						0.841	0.847	0.76						0.89	0.897	0.696
I felt at ease during the interaction	0.83	4.931	1.237	0.387	−0.313				0.844	4.737	1.467	−0.292	−0.305			
I felt comfortable during the interaction	0.903	5.426	1.12	−0.081	−0.434				0.882	5.011	1.261	0.887	−0.63			
I felt relaxed during the interaction	0.88	5.297	1.223	−0.254	−0.457				0.881	5.225	1.173	−0.031	−0.464			
Familiarity hotel robots						1	1	1						1	1	1
How would you rate your familiarity with service robots in hotels?	1	3.2	1.641	−0.651	0.368				1	3.23	1.865	−0.809	0.56			

TABLE 5 | Fornell Larcker test.

	Human–human interaction							Human–robot interaction						
	1	**2**	**3**	**4**	**5**	**6**	**7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1. Social Presence	**0.89**							**0.895**						
2. Satisfaction	0.80	**0.94**						0.766	**0.895**					
3. Behavioral Intention	0.79	0.868	**0.957**					0.742	0.873	**0.937**				
4. Inviting	0.79	0.76	0.747	**0.90**				0.71	0.798	0.765	**0.858**			
5. Comfort	0.838	0.81	0.788	0.829	**0.845**			0.714	0.808	0.801	0.784	**0.834**		
6. Care	0.74	0.78	0.787	0.73	0.753	**0.87**		0.604	0.76	0.793	0.699	0.74	**0.869**	
7. Familiarity Hotel Robots	0.03	0.02	−0.047	0.07	0.06	0.04	**1**	0.33	0.198	0.161	0.102	0.175	0.166	**1**

Note: Bold-faced diagonal elements are the square root of the variance shared between constructs and their measures. Off-diagonal elements represent correlations between constructs.

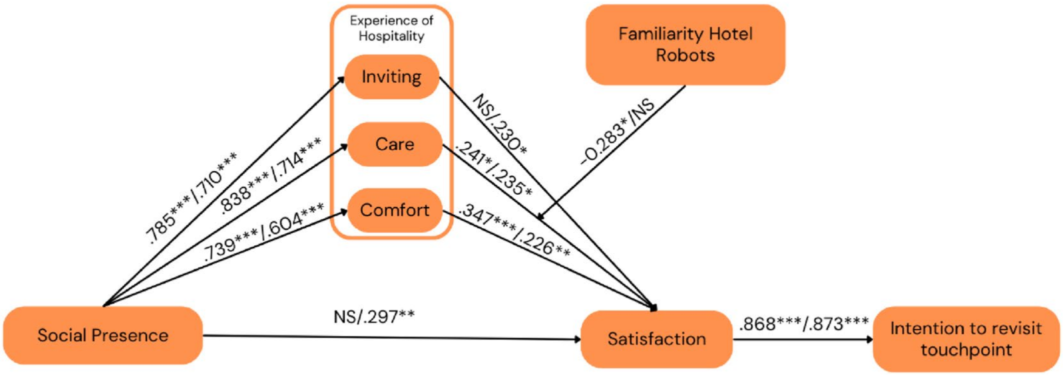

FIGURE 3 | Results of the two structural models. Path coefficients are displayed as human–human/human–robot; * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. [Color figure can be viewed at wileyonlinelibrary.com]

models from (Henseler, Ringle, and Sarstedt 2016) and established configural invariance, compositional invariance, and the equality of means and variances. After establishing these requirements, we performed two multi-group analyses: a PLS-based multi-group analysis and a parametric test (Henseler, Ringle, and Sarstedt 2016). PLS multi-group has been used in tourism literature (Jiménez-Barreto et al. 2020; Kim, So, and Wirtz 2022). A parametric test can be applied when results assume equal variance across groups (Henseler, Ringle, and Sarstedt 2016). In our study, differences in significance were found in the path between inviting and satisfaction (insignificant in the human–human case, significant in the human–robot case) and in the moderating effect of familiarity with service robots on the paths between care and satisfaction (significant in the human–human case, insignificant in the human–robot case). Multi-group analyses, however, show that only the moderating path coefficients differ significantly between the groups, hypothesis H1a–H3a were therefore rejected. The *p*-values of both multi-group analyses are displayed for each direct path in Table 8.

5 | Discussion and Implications

This study examines the impact of robotic versus human service agents on hospitality experience and factors of competitiveness, such as guest satisfaction and revisit intentions, with 200 participants in a real-life hotel setting. Our results reveal indifferent effects between human and robot agents in affecting guest satisfaction, which in turn influences the likelihood of revisiting the touchpoint. This finding aligns with previous (nonfield) research suggesting that robots can support service tasks without detracting from perceived experience (Belanche, Casaló, and Flavián 2021). Our data suggest that service robots can efficiently complement human staff without compromising guest experiences, offering cost savings and addressing staff shortages. This provides empirical support to previous theoretical claims about the economic advantages of robots in hospitality, marking a significant contribution to the debate on service robots' role in enhancing service productivity and competitiveness.

Our study demonstrates that, within a hybrid setting, service robots can be introduced without diminishing guest experience. This answer to our research question challenges the notion that robotic service detracts from guest engagement and satisfaction, suggesting instead that in the information provision context, human-like robots yield comparable experience of hospitality across all dimensions of inviting, comfort and care. This finding is particularly noteworthy for the dimension of care, where a stronger preference for human–human interactions might typically be expected. These insights suggest that service robots can

TABLE 6 | Structural model results.

		Human–human interaction					Human–robot interaction				
Hypothesis	**Path**	**Path coefficients**	***p***	***f*-square**	**95% confidence interval**	**Hypothesis supported?**	**Path coefficients**	***p***	***f*-square**	**95% confidence interval**	**Hypothesis supported?**
H1	Social presence → Inviting	0.785	0 ***	1.602	[0.688–0.858]	Yes	0.71	0 ***	1.016	[0.615–0.796]	Yes
H1	Social Presence → Care	0.838	0***	2.366	[0.742–0.904]	Yes	0.714	0 ***	1.038	[0.607–0.808]	Yes
H1	Social Presence → Comfort	0.739	0 ***	1.205	[0.633–0.827]	Yes	0.604	0 ***	0.574	[0.445–0.746]	Yes
H2	Social Presence → Satisfaction	0.248	0.055	0.066	[−0.015–0.501]	Yes	0.297	0.001**	0.153	[0.137–0.48]	Yes
H3	Inviting → Satisfaction	0.079	0.363	0.007	[−0.087–0.252]	No	0.23	0.03*	0.072	[0.022–0.44]	Yes
H3	Care → Satisfaction	0.241	0.05	0.052	[−0.018–0.476]	Yes	0.236	0.037*	0.074	[0.008–0.444]	Yes
H3	Comfort → Satisfaction	0.347	0 ***	0.185	[0.167–0.531]	Yes	0.226	0.009**	0.092	[0.06–0.403]	Yes
H5	Familiarity hotel robots × Inviting → Satisfaction	0.022	0.783	0.001	[−0.141–0.181]	No	0.032	0.756	0.002	[−0.211–0.183]	No
H5	Familiarity hotel robots × Care → Satisfaction	−0.283	0.014*	0.082	[−0.501–0.048]	No****	0.078	0.454	0.011	[−0.106–0.305]	No
H5	Familiarity hotel robots × Comfort → Satisfaction	0.185	0.079	0.05	[−0.022–0.395]	No	−0.112	0.153	0.022	[−0.272–0.041]	No
H6	Satisfaction → Behavioral Intention	0.868	0 ***	3.055	[0.815–0.912]	Yes	0.873	0 ***	3.198	[0.821–0.913]	Yes

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; ****path coefficient in the opposite direction as the hypothesis.

TABLE 7 | Path coefficients of the indirect effects.

Hypothesis	Path	Human–human case				Human–robot case			
		Path coefficients	p	95% confidence interval	Hypothesis supported?	Path coefficients	p	95% confidence interval	Hypothesis supported?
H4	Social Presence → Inviting → Satisfaction	0.062	0.367	[−0.07–0.199]	No	0.163	0.037*	[0.015–0.325]	Yes
H4	Social Presence → Care → Satisfaction	0.202	0.049 *	[−0.016–0.397]	Yes	0.168	0.034*	[0.005–0.311]	Yes
H4	Social Presence → Comfort → Satisfaction	0.256	0 ***	[0.125–0.393]	Yes	0.137	0.014*	[0.036–0.255]	Yes

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

improve operational efficiency without adversely impacting satisfaction or perceived experience of hospitality.

5.1 | Theoretical Implications

Our study focuses on two main areas: (1) robotization of guest journeys in hospitality service settings and (2) impact of service robots on hospitality experience in the moment.

First, our study joins debates concerning *robotizing guest journeys* in hospitality service settings (Tussyadiah, Zach, and Wang 2020). Specifically, we contribute to this discussion by investigating whether the touchpoint of information provision can be robotized without negatively impacting guest experience or satisfaction. By focusing on a single, clearly defined touchpoint, our study allows for targeted insights into the conditions under which robotic service agents can operate effectively, thereby impacting business competitiveness factors (i.e., satisfaction and revisiting intentions) (Tueanrat, Papagiannidis, and Alamanos 2021). Methodologically, our study complements existing conceptual studies and studies using secondary data and hypothetical scenarios.

Our results suggest the indifferent effects of service agents (human vs. concierge robot) on the perceived experience of hospitality. This finding challenges earlier studies, such as those by Choi et al. (2020), who report guests' preference for human agents in hospitality tasks. These studies, however, were based on methods where participants were shown pictures of robots and subsequently indicating preferences for human–human interactions. For interpretation, we refer to recent studies evidencing that guests' intention to use service robots is higher for utilitarian values (compared to hedonic values) (Ozturk et al. 2023; Zhang et al. 2024).

The nature of the studied touchpoint appears decisive when interpreting the indifference of service agents' impact on the hospitality experience. By focusing on information provision—a task with clear functional boundaries—we demonstrate how robotic agents can perform effectively in defined operational contexts. This paves the way toward a more nuanced understanding of (a) where (i.e., at which touchpoints throughout the guest journey) robots can be integrated as service agents and (b) what effects robot-automated touchpoints have on the perceived hospitality experience, potentially increasing efficiency and competitiveness at the hospitality frontline (Grönroos and Ojasalo 2004).

Our findings stem from a field study where the guests could choose between the mode of the service agent. Consequently, while we anchor in discussions around robotized guest journeys, our study specifically complements argumentation regarding service settings in which guests can proactively and independently choose between a human and a robot service agent for experiencing hospitality touchpoints.

Second, we anchor our discussions around the concept of *hospitality experience in the moment*, that is, perceived experience at a specific touchpoint within the customer journey (Becker and Jaakkola 2020; Kranzbühler et al. 2018). We purposefully take a snapshot perspective to capture the impact of service agents

TABLE 8 | Results of the multi-group tests.

Hypothesis	Path	PLS MGA	Parametric test	Hypothesis supported?
H1a	Social presence → Inviting	0.237	0.241	No
H1a	Social Presence → Care	0.06	0.06	No
H1a	Social Presence → Comfort	0.139	0.147	No
H2a	Social Presence → Satisfaction	0.751	0.755	No
H3a	Inviting → Satisfaction	0.268	0.27	No
H3a	Care → Satisfaction	0.966	0.977	No
H3a	Comfort → Satisfaction	0.339	0.34	No
H6	Satisfaction → Behavioral Intention	0.887	0.887	Yes
H5	Familiarity hotel robots × Inviting → Satisfaction	0.898	0.94	Yes
H5	Familiarity hotel robots × Care → Satisfaction	0.021	0.021*	No
H5	Familiarity hotel robots × Comfort → Satisfaction	0.022	0.024*	No

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

(human vs. robot) on the experience of a specific and isolated touchpoint (i.e., information provision). We add to the existing literature on the perception and adoption likelihoods of service robots in the frontline (e.g., Belanche, Casaló, and Flavián 2021; Choi et al. 2020; Hoang and Tran 2022). We study the impact of service robots right after the guest experiences the touchpoint of information provision. Thereby, we extend ongoing discussions around guests' acceptance and preferences for the type of service agents at specific touchpoints beyond measuring perceptions. By measuring guests' intention to revisit a service robot touchpoint, our study provides more realistic insights into the potential of robots at hospitality frontlines.

Our study provides new insights into the factors influencing hospitality experience at information touchpoints, confirming the importance of social presence for both robotic and human service agents (Kim and So 2022). Contrary to existing literature (Lu, Cai, and Gursoy 2019; Seo 2022), we found that familiarity with service robots does not enhance the guest's experience or satisfaction in robotized interactions. Interestingly, in human–human interactions, familiarity with robots negatively influenced guest satisfaction, suggesting that guests with more experience with robots may have higher expectations from human service, leading to potential dissatisfaction. This complexity highlights that in hybrid service environments, guests may form specific preferences for human and robotic agents depending on previous encounters and touchpoint context. These findings underscore the need for strategic deployment of service robots in hospitality settings.

5.2 | Practical Implications

Our study explored concierge robots' impact on hospitality experiences, particularly at information touchpoints, and found no significant difference in guest perception between robotic and human agents. This suggests that concierge robots can effectively complement human staff in providing information, offering a solution to personnel shortages (AHLA 2022) and potentially enhancing competitiveness through increased service productivity without compromising the guest experience. Implementing robots like Temi requires consideration of initial and ongoing costs, including programming for up-to-date information and maintenance.

Programming for venue-specific information is time-consuming and needs continuous updates, necessitating either third-party support or training for existing hospitality staff. While current concierge robots like Pepper, Temi, or Nao offer versatile functions, they are not yet ready for all hospitality tasks, such as handling payments or managing check-ins. Therefore, integrating service robots involves managing a service triad: human employees, robots, and guests, challenging practitioners to co-create hospitality experiences that leverage both human and robotic strengths (Homburg, Jozić, and Kuehnl 2017; Lemon and Verhoef 2016). Lastly, hybrid or fully robotized touchpoints impact job profiles of hospitality staff. Hence, while robots can mitigate staff shortages, additional tasks for human staff (i.e., programming, maintaining robot functionality) can mitigate the operational efficiencies. Thus, transitioning toward robot-assisted hospitality requires a strategic approach to defining the robot's role, ensuring cost-effectiveness, and supporting both service quality and guest satisfaction.

6 | Conclusions, Limitations, and Future Research

Our study provides insights into the effects of service robots versus human staff on customer journeys and guest experiences, challenging the prevailing notion of the negative impact of robotized touchpoints on competitiveness. We found indifferent effects in hospitality experiences between interactions with human and robotic agents at information points. This suggests that robots could reduce frontline human staff needs and associated costs without detracting from satisfaction, ultimately increasing competitiveness of hospitality business in the digital era.

However, our study focused solely on the information provision touchpoint, highlighting the need for broader research across various guest interactions to generalize findings. Specifically, with a sample size of 200 participants in a single venue, our findings should be regarded as preliminary steps towards generalization in real-life settings. Also, future studies should include a more diverse age range to better understand how different demographic factors impact guest interactions with robotic and human service agents.

We measured familiarity as a unified construct encompassing both experiential and perceptual aspects, and future research is needed to investigate the potentially distinct impacts of these dimensions on hospitality experience. Future studies should explore the broader implications of service robots throughout the guest journey and across different hospitality contexts to understand the nuances of human–robot interactions. Our single-venue study motivates further investigation into the role of contextual factors in robot effectiveness.

We call for future research to examine the decision-making process of guests choosing between human and robot service agents and to explore the potential of robots in handling more complex hospitality tasks. This would enrich our understanding of service robots' role in enhancing hospitality experiences, operational efficiency, and competitiveness in the hospitality industry.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Research data are not shared.

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