"I am served by a Robot!": internal antecedents of customer acceptance of robotic hotel-service agents

Journal of Organizational Change Management

Received 4 August 2023
Revised 25 October 2023
25 February 2024
Accepted 8 April 2024

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Abstract

Purpose – This study explores how customers' individual characteristics and perceptions affect acceptance of service robots as a hotel workforce. The Interactive Technology Acceptance Model (iTAM) has inspired us to investigate effects of customers' technological self-efficacy, perceived interactivity, sense of utility, and enjoyment-level of acceptance related to hotel-service robots as staff.

Design/methodology/approach – Data were collected from 224 customers via an online questionnaire conducted in the period April–June 2022 by convenience sampling, and then analyzed by using partial least squares – structural equation modeling (PLS-SEM).

Findings – The findings show that customers' technological self-efficacy and perceived interactivity with service robots enhances perceived usefulness and perceived enjoyment, serving as functional and emotional value components of service robots. They also demonstrate that robot's interactivity outweighs other robot's value components, such as perceived usefulness and perceived enjoyment for acceptance of service robots as employees in hotels.

Originality/value – While empirically validating the iTAM, this study emphasizes service robot interactivity as the most important aspect for customers' acceptance, and it adds a new perspective regarding the underexplored role of the customer-robot interface. Combining specific dimensions from different technology acceptance models (functional/socio-emotional/relational; utilitarian/hedonic) the study contributes to the service robot literature currently missing a more holistic understanding of consumers' experience and adoption drivers, and it provides managerial guidance on how to successfully implement service robots in hotel environments.

Keywords Interactive technology acceptance model (iTAM), Service robot, Customer technological self-efficacy, Customer-service robot perceptions, Customer-service robot acceptance

Paper type Research paper

Introduction

AI, robotics, and automation's growth has notably reshaped business, employee, and client interactions, especially in service sectors (Wirtz *et al.*, 2018; Huang *et al.*, 2021; Belanche *et al.*, 2020; Tung and Law, 2017) and the tourism and hospitality industries (Zhong *et al.*, 2021; Ivanov *et al.*, 2017; Buhalis and Leung, 2018; Tung and Au, 2018). These industries anticipate that technological advancements may improve efficiency, productivity, customer satisfaction, and solve workforce challenges (Leung, 2019; Del Guidice *et al.*, 2021; Wirtz *et al.*, 2018; Kumar *et al.*, 2019).

This research was supported by the National Science and Technology Council (NSC-111-2410-H-230-002).

Journal of Organizational Change Management

0953-4814
DOI 10.1108/JOCM-08-2023-0315

The integration of AI into robot development has transformed hotel operations, introducing service robots for tasks like check-in and guest services, particularly emphasizing contactless interactions since Covid-19 (Ivanov *et al.*, 2017; Chen *et al.*, 2021a, b; Huang *et al.*, 2021). This automation trend, seen in examples like Henn-na Hotel and Flyzoo Hotel, aims to improve guest experiences and efficiency (Buhalis and Leung, 2018; Lin and Mattila, 2021; Leung, 2022). The use of humanoid robots and digital assistants, responding to safety concerns, also mirrors the academic interest in leveraging technology to enhance hospitality services (Hotel Technology News, March 2019; Vrontis *et al.*, 2021; Tuomi *et al.*, 2020a, b; Choi *et al.*, 2019).

Service robots, as autonomous systems facilitating interaction and service delivery, are reshaping service sectors (Wirtz *et al.*, 2018; Mende *et al.*, 2019). They are adept at simple tasks, enhancing consistency and efficiency in service (Fuentes-Moraleda *et al.*, 2020; Engelberger, 2012; Del Guidice *et al.*, 2021), thus freeing staff to focus on customer relationships (Benmark and Venkatachari, 2016). Particularly in hospitality, they contribute to operational efficiency, decrease labor costs, offer instantaneous services, and elevate worker satisfaction (Lin and Mattila, 2021; Zhong *et al.*, 2021). Moreover, they heighten guest interest and minimize perceived risks and waiting periods, benefiting those who prioritize speed and convenience (Ivanov *et al.*, 2017; Buhalis and Sinatra, 2019; Najberg, 2018).

Service robots offer personalized and consistent customer service, potentially surpassing human employees in some aspects (Weiss *et al.*, 2009). However, their perceived service capability is not always superior, particularly in complex emotional scenarios where human interaction is preferred (Choi *et al.*, 2019; Wirtz *et al.*, 2018; Del Giudice *et al.*, 2021). Presently, hotel service robots lack advanced empathic intelligence (Huang and Rust, 2018), marking a clear distinction in the experience of interacting with robot receptionists compared to human staff (Tuomi *et al.*, 2020a, b).

Van Doorn *et al.* (2017) predict that by 2025, technology will significantly shape service experiences, especially in fostering relationships between service robots and humans (Fuentes-Moraleda *et al.*, 2020). Despite debates around new technologies in business (Leung, 2022), the interaction between service recipients and robots is crucial for a traveler's emotional bond with a hotel and its brand (Hwang and Seo, 2016; Fuentes-Moraleda *et al.*, 2020). Consequently, it's vital for hotel industries to comprehend Human-Robot Interaction (HRI) (Choi *et al.*, 2019) and the customer's acceptance of robots as service providers (Zhong *et al.*, 2021) to effectively deploy this technology.

Recent studies in service robotics, notably emphasizing empirical evidence (Lin and Mattila, 2021; Belanche *et al.*, 2020), signify a departure from conventional service quality research, addressing aspects like productivity, resistance (Fu *et al.*, 2022), and costs (Ivanov and Webster, 2019). This new trend focuses on improving customer experiences in the hospitality industry through robotics (Huang *et al.*, 2021), examining consumer attitudes and reactions to these technologies (Lin and Mattila, 2021; Huang, 2022). With the importance of investment returns, understanding consumer acceptance of novel technologies is key (Vrontis *et al.*, 2021), highlighting the need for insights on customer interactions with robots and acceptance factors (Huang *et al.*, 2021; Fuentes-Moraleda *et al.*, 2020; Huang, 2022; Zhong *et al.*, 2021). However, the focus on consumer perspectives is still limited (Kipnis *et al.*, 2022), which is vital for understanding customer experiences and choices regarding service robots (McLeay *et al.*, 2021; Tung and Au, 2018; Gretzel and Murphy, 2019; Go *et al.*, 2020).

This study addresses the factors influencing hotel customers' acceptance of service robots, utilizing the Technology Acceptance Model (iTAM) (Go *et al.*, 2020). It examines how guests' technological self-efficacy and their perceptions of service robot value impact their acceptance of these robots as hotel employees (Zhong *et al.*, 2021). The core research question is: “What is the effect of guests’ technological self-efficacy and perceptions of hotel-service robots on their acceptance of these robots as hotel employees?”

This study utilized questionnaires to explore how self-efficacy and perceptions of service robots influence their acceptance in hotels. It underscores the importance of understanding guest perspectives on service robots (Wirtz *et al.*, 2018; Choi *et al.*, 2019; Fuentes-Moraleda *et al.*, 2020) and their adoption (Lin and Mattila, 2021; Vrontis *et al.*, 2021). This research is key for improving service experiences and robot design, assisting hotel managers in enhancing service quality and guest interactions with service robots.

Literature review

Interactive technology acceptance model (iTAM)

This section synthesizes technology acceptance literature to underpin the model probing hotel-service robot adoption. It leverages iTAM (Go *et al.*, 2020) insights for nuanced understanding of robot acceptance (Zhong *et al.*, 2021), blending consumer behavior with technology adoption theories (Go *et al.*, 2020). iTAM integrates elements from seminal frameworks like TAM (Davis, 1985), TAM2 (Davis, 1989; Venkatesh and Davis, 2000), and UTAUT (Venkatesh *et al.*, 2003), highlighting their pivotal influences.

The Technology Acceptance Model (TAM), rooted in behavioral psychology, forecasts the acceptance of new technologies, highlighting the connections among users’ attitudes, intentions, and beliefs (Bonfanti *et al.*, 2023). The Interactive Technology Acceptance Model (iTAM) builds on TAM, integrating the dynamic and social facets of interactive technologies. It underscores the importance of real-time interactions, bidirectional communication, emotional responses, and social feedback in shaping the adoption of innovative technologies.

The TAM primarily considers individual utility but neglects various consumption values and the impact of emotions on technology adoption (Kang *et al.*, 2021; Richter *et al.*, 2023; Saber Chtourou and Souiden, 2010). Conversely, the iTAM introduces hedonic factors such as pleasure, enjoyment, playfulness, and fun (Go *et al.*, 2020; Fang *et al.*, 2005; Pagani, 2004), embracing a wide range of emotional reactions, including joy and anxiety, that are pivotal in users’ adoption choices. This makes iTAM a more comprehensive model, reflecting the dynamics of consumer behavior theories (Sheth *et al.*, 1991; Saber Chtourou and Souiden, 2010; Tanrikulu, 2021) by acknowledging emotions’ influence on the intention and behavior towards technology usage (Richter *et al.*, 2023).

The iTAM model extends TAM, focusing on personal technology adoption and integrating individual traits, technology perceptions, and usage intentions. It encompasses technology attributes, personal characteristics, and perceptions (Wang *et al.*, 2023; Rondan-Cataluña *et al.*, 2015), highlighting cognitive, emotional, and relational aspects of interaction with technology. This approach not only considers utilitarian factors like usefulness but also emotional and hedonic elements, exploring broader dimensions of human-technology relationships (Go *et al.*, 2020; Wirtz *et al.*, 2018; Fuentes-Moraleda *et al.*, 2020; Lu *et al.*, 2019; Gursoy *et al.*, 2019).

This research focuses on the general acceptance of hotel-service robots, deliberately omitting specific technological features, as per Go *et al.* (2020). While Dickinger *et al.* (2008) highlighted social norms as key to perceived usefulness and enjoyment, and Venkatesh and Bala (2008) underscored social influence and technology traits in their model, this study concentrates solely on personal factors like self-efficacy and individual technology perceptions, excluding social norms and technological attributes.

Technological self-efficacy and perceptions of hotel service robots

Self-efficacy (SE), as per Bandura (1997), is one’s belief in their capability to execute tasks in specific contexts, emphasizing perceived over actual abilities. Within technology, SE assesses individuals' proficiency with computers (Compeau and Higgins, 1995), software (Agarwal *et al.*, 2000; Hasan, 2006), the Internet (Eastin and LaRose, 2000; Hsu and Chiu, 2004), and robots (Turja *et al.*, 2019). Notably, higher computer SE is linked to more engagement and enjoyment, and less anxiety (Compeau and Higgins, 1995). Similarly, greater robot SE suggests more confidence in robot interactions (Turja *et al.*, 2019). It appears SE crucially influences technology acceptance (Teo, 2009) and indirectly affects perceived usefulness and satisfaction (Teo, 2009).

In iTAM, perceived usefulness is the belief in a technology's effectiveness in achieving goals (Go *et al.*, 2020). Influenced by factors like functionality, benefits, and past experiences, this perception is heightened in individuals with high self-efficacy (SE). High SE fosters confidence in effectively utilizing technology (Teo, 2009; Fan *et al.*, 2020).

Enjoyment reflects a positive emotional response to activities (Go *et al.*, 2020) and is influenced by design, challenges, and utility in technology (Chen *et al.*, 2021a, b). Higher technological self-efficacy (SE) is linked to greater enjoyment and mastery. This research investigates technology acceptance, emphasizing initial self-efficacy with robot technology, leading to the formulation of two hypotheses.

H1. Self-efficacy (SE) positively affects the perceived usefulness (PU) of the service robot.

H2. Self-efficacy (SE) positively affects the perceived enjoyment (PE) of the service robot.

Advancements in AI and big data are increasingly enhancing robots in the hospitality industry, showing significant benefits (Leung, 2022; Zhong *et al.*, 2020). Yet, these robots often lack advanced interactive capabilities, especially in scenarios requiring deep cognitive and emotional involvement (Del Giudice *et al.*, 2021). They face difficulties in service situations demanding judgment, intuition, and empathy (Chiang and Trimi, 2020). Furthermore, their malfunctions may lead to customer dissatisfaction, notably when human staff are absent (Choi *et al.*, 2021).

Recent research highlights human-robot interactions in service settings, emphasizing their impact on service quality perceptions, notably in hospitality (Yan *et al.*, 2014; de Graaf *et al.*, 2015; Guenzi and Pelloni, 2004). The feeling of a robot's "presence" and its social behaviors significantly influence user acceptance and perceived usefulness (Wirtz *et al.*, 2018; McLean and Osei-Frimpong, 2019). Evaluating a robot's Perceived Interactivity (PI) is key for service effectiveness (Go *et al.*, 2020; Choi *et al.*, 2019), and advanced robot designs could enhance complex service delivery (Go *et al.*, 2020; Fuentes-Moraleda *et al.*, 2020).

Perceived enjoyment (PE), essential in technology adoption, derives from the enjoyment of using technology, not just outcomes (Davis *et al.*, 1992). Studies show a robot's communication style significantly affects users' feelings (Tung and Au, 2018; Fuentes-Moraleda *et al.*, 2020), with proper interactions enhancing enjoyment, especially in services like hospitality. Robots' abilities in voice and gesture recognition contribute to these positive experiences (Tung and Au, 2018). The evident excitement in children during robot interactions highlights the importance of playfulness (Tung and Au, 2018), suggesting the value of understanding social behaviors in Human-Robot Interaction for developing enjoyable robots (Collins, 2020; Fuentes-Moraleda *et al.*, 2020).

H3. Perceived interactivity (PI) positively affects perceived usefulness (PU) of the service robot.

H4. Perceived interactivity (PI) positively affects perceived enjoyment (PE) of the service robot.

Acceptance of service robots as employees

Organizations adopt technology to boost competitiveness, but this does not guarantee its use (Huang *et al.*, 2019; McFarland and Hamilton, 2006). iTAM proposes acceptance as a three-phase journey, where both technology and individual traits prompt cognitive reactions (like perceptions of innovation, usefulness, and enjoyment), influencing attitudes and eventually leading to acceptance (Saber-Chtourou and Souiden, 2010; Go *et al.*, 2020; Davis, 1993).

Robots are becoming vital in hospitality, transforming customer service (Pinillos *et al.*, 2016). Robot receptionists play a key role in shaping guests' satisfaction and first impressions (Leung, 2022). Positive interactions with these robots can positively affect consumer evaluations (Bartneck *et al.*, 2009). The design and functionality of service robots are crucial in determining guests' initial and overall impressions (Leung, 2022; Tung and Au, 2018; Fuentes-Moraleda *et al.*, 2020). It's important to consider guests' views on robotic services, as the effectiveness of these robots in hotels depends on the quality of interaction and the enjoyment they provide (Choi *et al.*, 2019).

H5. Perceived interactivity (PI) of the robot positively affects accepting service robots as employees (RAE).

The usefulness and enjoyment of technology are key to its acceptance. Usefulness is seen as how technology aids task performance (Liu *et al.*, 2022), and enjoyment is the pleasure from its use, aside from performance benefits (Davis *et al.*, 1992). These factors influence the willingness to adopt technology (Saber-Chtourou and Souiden, 2010). For example, perceived advantages of service robots, like improved service quality in human-robot interactions (Kharub *et al.*, 2021), increase guests' likelihood of using them. Therefore, recognizing technology's value is crucial for its adoption (Liu *et al.*, 2022).

Research suggests the significance of enjoyment in technology adoption, notably in online gaming and robotics (Go *et al.*, 2020; Venkatesh *et al.*, 2002). This study suggests that Perceived Enjoyment (PE) is vital for accepting technologies such as robots. It indicates that robot characteristics indirectly influence user preferences towards human-like robots (Fuentes-Moraleda *et al.*, 2020; Kätsyri *et al.*, 2015).

H6. Perceived usefulness (PU) of the robot positively affects accepting service Robots as Employees (RAE).

H7. Perceived enjoyment (PE) of the robot positively affects accepting service Robots as Employees (RAE).

Figure 1 presents a research framework proposed in this work. The framework is developed to have five key concepts and seven hypotheses to study the user acceptance of hotel-service robots as employees within the hotel industry.

Methodology

Data collection and sample

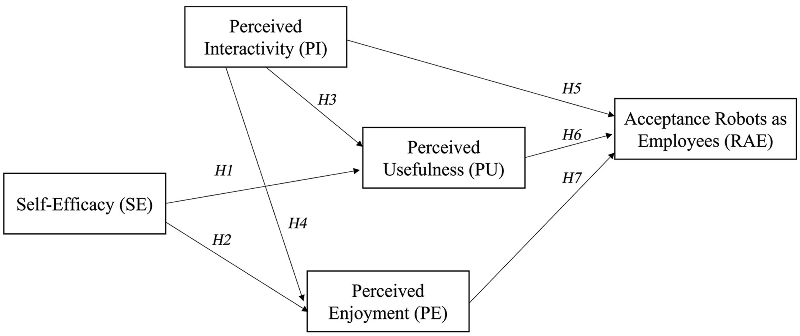
The study employed an online survey to collect data from users with varying levels of experience with hotel-service robots, following the approaches of Zhong *et al.* (2021) and Lu *et al.* (2019). Due to the limited promotion of service robots in hotels, finding experienced participants was challenging (Zhong *et al.*, 2021). Nonetheless, research by Di Pietro *et al.* (2015) and Deb *et al.* (2017) suggests that prior experience with technology slightly influences acceptance attitudes. The Technology Acceptance Model (TAM) and its extensions are suggested for examining technology acceptance, especially in early adoption stages (Sánchez-Prieto *et al.*, 2017).

The study sought to collect survey data from a wide range of demographics and travel intentions, from Baby Boomers to Generation Z, covering business, leisure, and wellness trips. A tourism expert on the team pinpointed key sites in Kaohsiung, including a theme park, malls, an art museum, hotels, and a spa resort, for data collection, where data collection permissions were obtained. QR codes and survey summaries were prominently displayed, yielding 224 valid responses between April and June 2022, with participant demographics presented in Table 1.

Survey instrument and measurement

The questionnaire comprised three sections, starting with respondents' background details like age, gender, and nationality. This approach aligns with research indicating varied preferences for hotel-service robots among different demographic groups (Zhong *et al.*, 2021). Additionally, cultural context influences customer perceptions and acceptance of service robots, affecting their practical implementation (Tuomi *et al.*, 2020a, b; Fuentes-Moraleda *et al.*, 2020).

The second section focused on the consumption values of respondents regarding hotel stays and their experience with robot services in hotels, such as encountering service robots



Source(s): Authors' work

Figure 1. Acceptance model from the customer's perspective – hotel-service robots as employees

Table 1. Sample characteristics

	Freq.	%		Freq.	%
Age			*Nationality*		
<25	155	69	Southeast Asia	122	54
25–45	49	22	East Asia	45	20
>45	20	9	Europe	24	11
Total	*224*	*100*	Others	33	*15*
			Total	*224*	*100*
Gender			*Experience with service robots*		
Male	80	36	With experience	80	36
Female	137	61	Without experience	144	64
Prefer not to say	7	3	*Total*	*224*	*100*
Total	*224*	*100*			

Note(s): Southeast Asia (Indonesia, Thailand, Vietnam, Philippines, Malaysia); East Asia (Taiwan, Japan, Hong Kong); Europe (Serbia, Macedonia, Germany, Croatia, Italy, UK); Others (Australia, USA, Canada, Latin America)
Source(s): Authors' work

and the types they interacted with (front desk, room service, concierge, housekeeping, information, etc.) (Zhong *et al.*, 2021). It also clearly defined service robots in the hospitality sector, highlighting various models (check-in, cleaning, and food-delivery robots) employed within the industry.

The third segment of the survey focused on customer perceptions and acceptance of a hotel-service robot, emphasizing aspects like self-efficacy, perceived interactivity, usefulness, enjoyment, and the acceptance of robots as hotel employees. This part drew upon theoretical frameworks from various technology acceptance models, relevant to the hotel sector, and incorporated empirical studies to construct a questionnaire. It comprised 21 questions, all employing a five-point Likert scale, where higher scores indicated stronger agreement, ranging from "1–Strongly Disagree" to "5–Strongly Agree."

In our research on consumer readiness for service-delivery robots, we adopted Lu *et al.* (2019)'s scale development method, integrating insights from tourism, hospitality, information systems, and marketing. To validate our items, we engaged with three tech-aware academics in tourism and hospitality via semi-structured interviews. Conducted primarily in Taiwan, the study paid close attention to the questionnaire's language accuracy through back translation, as suggested by Chidlow *et al.* (2015), and refined the survey after a pilot test to enhance clarity and readability.

Measures

Self-efficacy refers to confidence in utilizing innovative technology, as Zhong *et al.* (2021) noted. Perceived Interactivity, as defined by Tung and Au (2018) and Wirtz *et al.* (2018), assesses a robot's responsiveness and social abilities, such as language recognition. Zhong *et al.* (2021) highlighted Perceived Usefulness, gauging a robot's efficiency in hotel services, focusing on timeliness and personalization. Perceived Enjoyment, influenced by Fuentes-Moraleda *et al.* (2020) and Tung and Au (2018), explores the enjoyment from interacting with service robots, considering emotional impacts. The concept of Robots as Employees Acceptance, drawing on insights from Zhong *et al.* (2021) and Lu *et al.* (2019), captures attitudes and perceived value through a specific scale. These concepts are outlined in Table 2.

Data analysis

Descriptive statistics

Our survey received 224 responses, predominantly from Southeast Asia (122 from Indonesia, Thailand, Vietnam, Philippines, Malaysia) and East Asia (45 from Taiwan, Japan, Hong Kong), with a smaller number from Europe (24 from Serbia, Macedonia, Germany, Croatia, Italy, UK) and other regions (33 from Australia, North America, South America). The bulk of replies were from Indonesia (62), Taiwan (42), and Thailand (34). The average participant age was 26.29, with a median age of 22, spanning 15–62 years. Further demographic details are provided in Table 1.

A majority of survey respondents had not used hotel-service robots (64%), though this study found a relatively higher proportion of those familiar with the technology (36%) compared to past research (Zhong *et al.*, 2021). Given the nascent stage of robot adoption in the hospitality sector, it's difficult to access a broad base of experienced users (Lu *et al.*, 2019; Zhong *et al.*, 2021). Of those acquainted, most knew information robots (23%), with fewer interactions reported with check-in/out (19%), room-service (11%), housekeeping (10%), and concierge robots (4%), suggesting a narrow range of encounters with different robot services.

	Convergent validity	Composite reliability	Cronb. Alpha	Dijkstra's rho	AVE
Self-efficacy (SE)					
SE 1 – I like computer programs	0.879	0.913	0.871	0.895	0.725
SE 2 – I find new technologies to be interesting	0.912				
SE 3 – Technology makes me more efficient	0.874				
SE 4 – In general, I am among the first in a circle of friends to acquire new technology	0.729				
Perceived interactivity (PI)					
PI 1 – Having a service robot complete my check-in would be a nice experience	0.759	0.887	0.829	0.842	0.662
PI 2 – Service robots are able to understand me and respond appropriately	0.844				
PI 3 – Asking a favor to service robots is more comfortable than asking it to a human worker	0.780				
PI 4 – Overall Interacting with a service robot during all my stay would be pleasant	0.867				
Perceived usefulness (PU)					
PU 1 – Service robots are able to deliver the right service	0.833	0.908	0.873	0.874	0.663
PU 2 – Service robots are able to fulfill all of my needs during the stay	0.830				
PU 3 – Service robots are able to deliver service in a timely manner/efficiently	0.823				
PU 4 – Service robots are able to deliver customized service	0.775				
PU 5 – Service robots are able to adapt to my different needs	0.810				
Perceived enjoyment (PE)					
PE 1 – The appearance of a service robot in a front desk is frightening (dropped)	0.917	0.914	0.811	0.823	0.841
PE 2 – Having a service robot to complete my check-in would be fun					
PE 3 – Overall experience with service robots would be satisfactory	0.917				
Robots as employees (RAE)					
RAE 1 – Robots are capable of replacing human staff in a hotel	0.759	0.865	0.804	0.838	0.561
RAE 2 – It is possible for a hotel to run only with robots as their service employees	0.719				
RAE 3 – I prefer hotels with robots or advanced machines (i.e. auto check-in kiosk, facial recognition door, etc.)	0.787				
RAE 4 – I believe by using robots as an employee my security and privacy will be more ensured	0.763				
RAE 5 – I will pay more to experience interacting with service robots in a hotel	0.715				

Source(s): Authors' work

Table 2.
Measurement model

PLS-SEM

The analysis utilized partial least squares – structural equation modeling (PLS-SEM), valued for its efficacy in managing data limitations and examining intricate variable interactions, such as mediation effects (Hair *et al.*, 2012), via WarpPLS 8.0. With 224 responses, the study's sample size surpassed the minimum thresholds of 160 and 146, determined by the inverse square root and gamma-exponential methods, aiming for a power level of 0.800.

To mitigate common method bias, the survey randomized constructs to obscure the model's structure. Harman's test showed minimal bias, with variance significantly under 50% (Podsakoff and Organ, 1986). Further, a collinearity assessment (Kock, 2015) revealed VIFs below critical thresholds, indicating negligible common method bias.

The reliability and validity test

The measurement model's reliability and validity were assessed, focusing on factor loadings for convergent validity via exploratory principal component analysis. All measures surpassed the 0.7 threshold for composite reliability and Cronbach's alpha, with scores ranging from 0.865 to 0.914 and alpha values from 0.804 to 0.873, respectively (Hair *et al.*, 2012). One item was removed from Perceived Enjoyment to maintain the average variance extracted above 0.5, following advice by Hair *et al.* (2013). Additionally, all constructs had Dijkstra's rho values exceeding 0.8.

Table 3 demonstrates the discriminant validity of our measurement model. It shows that the square root of the average variance extracted surpasses the inter-construct correlations, signifying adequate discriminant validity (Fornell and Larcker, 1981). Additionally, the heterotrait–monotrait (HTMT) ratio mostly falls below 0.9, aligning with recommended standards (Henseler *et al.*, 2015). Consequently, we assert that the model exhibits satisfactory discriminant validity.

The study examined variance inflation factors to identify potential multi-collinearity among variables, including moderators, finding all values below 5, as per Hair *et al.* (2012), suggesting minimal multi-collinearity concerns (see Table A1 in Appendix). Thus, it

		1	2	3	4	5
1	Self-Efficacy (SE)	*0.851*				
2	Perceived Interactivity (PI)	0.544	*0.814*			
3	Perceived Usefulness (PU)	0.596	0.683	*0.814*		
4	Perceived Enjoyment (PE)	0.616	0.800	0.709	*0.917*	
5	Robots as employees (RAE)	0.262	0.524	0.389	0.433	*0.749*
1	Self-Efficacy (SE)	1.000				
2	Perceived Interactivity (PI)	<0.001	1.000			
3	Perceived Usefulness (PU)	<0.001	<0.001	1.000		
4	Perceived Enjoyment (PE)	<0.001	<0.001	<0.001	1.000	
5	Robots as employees (RAE)	<0.001	<0.001	<0.001	<0.001	1.000

HTMT ratios

	SE	PI	PU	PE
Perceived Interactivity (PI)	0.639			
Perceived Usefulness (PU)	0.679	0.802		
Perceived Enjoyment (PE)	0.727	1.029	0.841	
Robots as employees (RAE)	0.316	0.638	0.463	0.534

Note(s): Square roots of AVE shown on diagonal
Source(s): Authors work

Table 3.
Discriminant validity

tentatively supports the measures' reliability and validity, enabling progression to the structural model, following Hair *et al.* (2012).

Structural model

In our structural model, we tested our hypothesis using a stable estimation method to establish the statistical significance of the paths (Kock, 2011). This stable method, as distinguished from simple bootstrapping, produces more stable path coefficients (Kock, 2014).

The model statistics results are promising and align with commonly used thresholds. For instance, the goodness of fit measure, Tenenhouse, is within the acceptable range of 0.606 (Wetzels *et al.*, 2009). Additionally, the predictive validity of the model is evident in the Q-squared values for the predicted variables, ranging from 0.296 to 0.750 (Kock, 2014).

Path coefficients and their associated *P* values have been meticulously documented in accordance with Kock's approach (2016). These *P* values not only signify the strength of relationships but also consider statistical power. It's important to note that even lower path coefficient values can maintain statistical significance, especially in datasets with a larger sample size.

Table 4 provides a summary of the hypothesis tested in this research study. The R-squared Perceived Interactivity (PI) was 0.33, for Perceived Enjoyment (PE) 0.75, for Perceived Usefulness (PU) 0.55, and for Robots as Employees (RE) 0.30.

Our analysis found significant support for Hypotheses 1 and 2, with positive path coefficients between SE and PI ($\beta = 0.260$, $p < 0.01$) and SE and PE ($\beta = 0.185$, $p < 0.01$), respectively. Likewise, the relationship between PI and PU (Hypothesis 3) was positively significant ($\beta = 0.550$; $p < 0.01$), a trend that continued for Hypotheses 4 ($\beta = 0.740$; $p < 0.01$), 5 ($\beta = 0.430$; $p < 0.01$), and 6 ($\beta = 0.160$; $p < 0.01$). In contrast, Hypothesis 7 did not achieve statistical significance, indicating a weak positive path coefficient ($\beta = 0.000$, $p = 0.47$).

We conducted additional analyses by incorporating control variables such as nationality, age, and gender of the respondents. Notably, these supplementary analyses did not alter the significance of our hypotheses. For a comprehensive presentation of the model's outcomes, including the effects of the control variables, please refer to Appendix.

Discussion

The study indicates that technological self-efficacy (SE) enhances evaluations of service robots, notably affecting Perceived Usefulness (PU) and Enjoyment (PE), with higher SE improving utility recognition and reducing apprehension (Go *et al.*, 2020; Fan *et al.*, 2020; Teo, 2009; Compeau and Higgins, 1995). SE more significantly influences PU than PE, suggesting a preference for functional over emotional benefits (Wirtz *et al.*, 2018; Lin and Mattila, 2021), implying hotels should account for guests' SE to improve tech acceptance.

	Path coefficient	*p*-value	Hypothesis supported
Hypothesis 1: SE and PU	0.260	<0.001	Yes
Hypothesis 2: SE and PE	0.185	<0.001	Yes
Hypothesis 3: PI and PU	0.550	<0.001	Yes
Hypothesis 4: PI and PE	0.740	<0.001	Yes
Hypothesis 5: PI and RAE	0.430	<0.001	Yes
Hypothesis 6: PU and RAE	0.160	<0.001	Yes
Hypothesis 7: PE and RAE	0.000	$p = 0.47$	No

Source(s): Authors' work

Table 4.
Hypothesis testing

Perceived Interactivity (PI) significantly influences user perceptions of technology, notably affecting Perceived Usefulness (PU) and Enjoyment (PE). It is vital in assessing a robot's first impression through responsiveness and control, marking an essential aspect of interface quality (Go *et al.*, 2020). While early studies prioritized PU in human-robot interaction, recent findings highlight the significance of emotional and relational factors (Fuentes-Moraleda *et al.*, 2020). PI is increasingly associated with the hedonic aspects of service robots, highlighting their role in fulfilling social-emotional and relational needs beyond mere functional performance (Lu *et al.*, 2019; Fernandes and Oliveira, 2021; Wirtz *et al.*, 2018; Lu *et al.*, 2019).

Our study shows interactivity is crucial for hotel guests' acceptance of service robots, more than usefulness or functionality, with minimal impact from perceived enjoyment, highlighting the importance of human-robot interaction in consumer experience, as supported by Fuentes-Moraleda *et al.* (2020). Emotional engagement and satisfaction with the hotel brand are significantly affected, per Brakus *et al.* (2009) and Hwang and Seo (2016). Practical benefits like efficiency are undervalued by consumers (Lin and Matilla, 2021), and the entertainment value of robots hardly affects acceptance across traveler demographics (Fuentes-Moraleda *et al.*, 2020).

Conclusion

The rise of service robots in hospitality (Huang *et al.*, 2021; Lin and Mattila, 2021; Belanche *et al.*, 2020; Lu *et al.*, 2019) prompted analysis on guest acceptance, utilizing the iTAM model. Our research indicates that technological self-efficacy and robot value perceptions crucially influence acceptance, highlighting the importance of technological confidence and interactivity. Interactivity, notably, boosts perceived enjoyment, underscoring acceptance's dependence on both social-emotional satisfaction and functionality (Fernandes and Oliveira, 2021; Wirtz *et al.*, 2018). These insights advocate for enhanced robot design and service, prioritizing interactivity to fulfill both utilitarian and hedonic requirements.

Theoretical implications

This research analyzes the acceptance of hotel-service robots using the technology acceptance model, integrating elements from the Service Robot Acceptance Model (sRAM) (Wirtz *et al.*, 2018), iTAM (Go *et al.*, 2020), TAM (Davis, 1989), Consumer Acceptance of Technology (Kulviwat *et al.*, 2007), and UTAUT (Venkatesh *et al.*, 2003, 2012), highlighting their considerable commonalities (Fuentes-Moraleda *et al.*, 2020). It provides an in-depth view of guest interactions with service robots, enriching an emerging research domain with empirical insights (Ivanov *et al.*, 2019; Fuentes-Moraleda *et al.*, 2020; Lin and Mattila, 2021). Emphasizing a customer-centric perspective, the study fills a crucial gap in the literature on consumer experiences and cognitive processes with service robots, making a substantial contribution to the discipline (Gretzel and Murphy, 2019; Huang *et al.*, 2021; Lin and Mattila, 2021; Tussyadiah, 2020).

Our framework integrates elements from the sRAM and iTAM models, emphasizing functional, socio-emotional, and relational dimensions by including Perceived Usefulness (PU), Perceived Interactivity (PI), and Perceived Enjoyment (PE). It covers iTAM's critical aspects: Self-Efficacy for individual traits, innovative technology perceptions via PI, PU, PE, and Acceptance of Robots as Employees. It also echoes Lu *et al.* (2019), combining cognitive (PU for robot efficacy) and emotional (PE for intrinsic motivation) aspects.

Practical implications

Research on technology acceptance is crucial for integrating service robots in future service industries (Zhong *et al.*, 2021). Hoteliers investing in technology must understand the synergy between humans and robots to enhance customer service and secure investment returns (Lin and Mattila, 2021; Huang *et al.*, 2021). Critical to designing effective service robots in hospitality and tourism is grasping customer perceptions towards these robots (Tussyadiah and Park, 2018; Tussyadiah, 2020). Investigating the factors influencing customer acceptance of service robots is therefore vital. Our study aids the tourism and hospitality industry by supporting better management of robot-enabled services and improving customer experiences with robots, potentially offering hotels a competitive edge in the digital age (Fuentes-Moraleda *et al.*, 2020).

Social implications

Social and service robots are increasingly prevalent, offering continuous service, companionship, efficiency, and cost reduction, notably in the labor-intensive hospitality sector. Literature on service robots highlights the significance of customer attitudes towards robotic staff for their wider acceptance and growth within the industry (Lin and Mattila, 2021; Huang *et al.*, 2021; Tussyadiah and Park, 2018).

This paper examines the use of robots in hotels, highlighting their role in economic and social sustainability for proprietors. Robots enhance service consistency and efficiency, vital for the competitiveness of the hospitality sector (Huang *et al.*, 2021). However, overreliance on robots might compromise hospitality's core values, affecting customer service quality (Choi *et al.*, 2019; Fusté-Forné and Ivanov, 2021; Pinillos *et al.*, 2016; Huang *et al.*, 2021). Automation and artificial intelligence advancements could reduce guest-staff interactions, potentially diminishing socialization and essential social values like empathy and environmental care (Tussyadiah, 2020).

Limitations and future research

Our study omitted the examination of how technological features influence customer perceptions and acceptance of service robots, a key aspect of the iTAM model (Go *et al.*, 2020). This omission includes not differentiating task performance among similar robots (Go *et al.*, 2020). Future research should consider technological traits, task focus, and appearance, along with perceived risk (Go *et al.*, 2020), trust (Wirtz *et al.*, 2018), and privacy concerns (Lin and Mattila, 2021), to better understand customer attitudes towards using service robots.

The ITAM model, while foundational, was supplemented with aspects from other models for this study. Future research should explore diverse models and create hospitality-focused frameworks and scales, addressing gaps identified by Ivanov *et al.* (2017) and Fuentes-Moraleda *et al.* (2020). Technology complements rather than replaces human capabilities (Lin and Mattila, 2021; Wilson and Daugherty, 2018). The emerging challenge for policymakers, scholars, and practitioners is managing the ethical and profitable coexistence between humans and robots (Fusté-Forné and Ivanov, 2021). Future research must address ethical human-robot interactions in service delivery, enhance human technological skills (Tuomi *et al.*, 2020a, b), and debate the ethical implications of digital technologies in human-centered environments (Müller, 2020).

References

Agarwal, R., Sambamurthy, V. and Stair, R.M. (2000), "Research report: the evolving relationship between general and specific computer self-efficacy—an empirical assessment", *Information Systems Research*, Vol. 11 No. 4, pp. 418-430, doi: 10.1287/isre.11.4.418.11876.

Bandura, A. (1997), *Self-efficacy: the Exercise of Control*, Freeman, New York.

Bartneck, C., Kulić, D., Croft, E. and Zoghbi, S. (2009), "Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots", *International Journal of Social Robotics*, Vol. 1 No. 1, pp. 71-81, doi: 10.1007/s12369-008-0001-3.

Belanche, D., Casaló, L., Flavián, C. and Schepers, J. (2020), "Service robot implementation: a theoretical framework and research agenda", *The Service Industries Journal*, Vol. 40 Nos 3/4, pp. 203-225, doi: 10.1080/02642069.2019.1672666.

Benmark, G. and Venkatachari, D. (2016), "Messaging apps are changing how companies talk with customers", *Harvard Business Review*, Vol. 23, available at: https://hbr.org/2016/09/messaging-apps-are-changing-how-companies-talk-withcustomers (accessed 30 November 2020).

Bonfanti, R.C., Tommasi, F., Ceschi, A., Sartori, R. and Ruggieri, S. (2023), "The Antecedents of the technology acceptance model in microentrepreneurs' intention to use social networking sites", *European Journal of Investigation in Health, Psychology and Education*, Vol. 13 No. 7, pp. 1306-1317, doi: 10.3390/ejihpe13070096.

Brakus, J.J., Schmitt, B.H. and Zarantonello, L. (2009), "Brand experience: what is it? How is it measured? Does it affect loyalty?", *Journal of Marketing*, Vol. 73 No. 3, pp. 52-62, doi: 10.1509/jmkg.73.3.52.

Buhalis, D. and Leung, R. (2018), "Smart hospitality—interconnectivity and interoperability towards an ecosystem", *International Journal of Hospitality Management*, Vol. 71, pp. 41-50, doi: 10.1016/j.ijhm.2017.11.011.

Buhalis, D. and Sinarta, Y. (2019), "Real-time co-creation and nowness service: lessons from tourism and hospitality", *Journal of Travel and Tourism Marketing*, Vol. 36 No. 5, pp. 563-582, doi: 10.1080/10548408.2019.1592059.

Chen, S.-H., Tzeng, S.-Y., Tham, A. and Chu, P.-X. (2021a), "Hospitality services in the post COVID-19 era: are we ready for high-tech and no touch service delivery in smart hotels?", *Journal of Hospitality Marketing Management*, Vol. 30 No. 8, pp. 905-928, doi: 10.1080/19368623.2021.1916669.

Chen, Y., Lin, Z., Filieri, R. and Liu, R. (2021b), "Subjective well-being, mobile social media and the enjoyment of tourism experience: a broaden-and-build perspective", *Asia Pacific Journal of Tourism Research*, Vol. 26 No. 10, pp. 1070-1080, doi: 10.1080/10941665.2021.1952285.

Chiang, A.H. and Trimi, S. (2020), "Impacts of service robots on service quality", *Service Business*, Vol. 14 No. 3, pp. 439-459, doi: 10.1007/s11628-020-00423-8.

Chidlow, A., Ghauri, P.N., Yeniyurt, S. and Cavusgil, S.T. (2015), "Establishing rigor in mail-survey procedures in international business research", *Journal of World Business*, Vol. 50 No. 1, pp. 26-35, doi: 10.1016/j.jwb.2014.01.004.

Choi, Y., Choi, M., Oh, M. and Kim, S. (2019), "Service robots in hotels: understanding the service quality perceptions of human-robot interaction", *Journal of Hospitality Marketing and Management*, Vol. 29 No. 6, pp. 613-635, doi: 10.1080/19368623.2020.1703871.

Choi, S., Mattila, A.S. and Bolton, L.E. (2021), "To err is human(-oid): how do consumers react to robot service failure and recovery?", *Journal of Service Research*, Vol. 24 No. 3, pp. 354-371, doi: 10.1177/1094670520978798.

Collins, G.R. (2020), "Improving human–robot interactions in hospitality settings", *International Hospitality Review*, Vol. 34 No. 1, pp. 61-79, doi: 10.1108/IHR-09-2019-0019.

Compeau, D.R. and Higgins, C.A. (1995), "Computer self-efficacy: development of a measure and initial test", *MIS Quarterly*, Vol. 19 No. 2, pp. 189-211, doi: 10.2307/249688.

Davis, F.D. (1985), "A technology acceptance model for empirically testing new end-user information systems: theory and results", Doctoral dissertation, Massachusetts Institute of Technology.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-340, doi: 10.2307/249008.

Davis, F.D. (1993), "User acceptance of information technology: system characteristics, user perceptions and behavioural impacts", *International Journal of Man Machine Studies*, Vol. 38 No. 3, pp. 475-487, doi: 10.1006/imms.1993.1022.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1992), "Extrinsic and intrinsic motivation to use computers in the workplace", *Journal of Applied Social Psychology*, Vol. 22 No. 14, pp. 1111-1132, doi: 10.1111/j.1559-1816.1992.tb00945.x.

de Graaf, M.M.A., Allouch, S.B. and Klamer, T. (2015), "Sharing a life with Harvey: exploring the acceptance of and relationship-building with a social robot", *Computers in Human Behavior*, Vol. 43, pp. 1-14, doi: 10.1016/j.chb.2014.10.030.

Deb, S., Strawderman, L., Carruth, D.W., DuBienSmith, J.B. and Garrison, T.M. (2017), "Development and validation of a questionnaire to assess pedestrian receptivity toward fully autonomous vehicles", *Transportation Research Part C: Emerging Technologies*, Vol. 84, pp. 178-195, doi: 10.1016/j.trc.2017.08.029.

Del Giudice, M., Scuotto, V., Ballestra, L.V. and Pironti, M. (2021), "Humanoid robot adoption and labour productivity: a perspective on ambidextrous product innovation routines", *The International Journal of Human Resource Management*, Vol. 33 No. 6, pp. 1-27, doi: 10.1080/09585192.2021.189764.

Di Pietro, L., Mugion, R.G., Mattia, G., Renzi, M.F. and Toni, M. (2015), "The integrated model on mobile payment acceptance (IMMPA): an empirical application to public transport", *Transportation Research Part C: Emerging Technologies*, Vol. 56, pp. 463-479, doi: 10.1016/j.trc.2015.05.001.

Dickinger, A., Arami, M. and Meyer, D. (2008), "The role of perceived enjoyment and social norm in the adoption of technology with network externalities", *European Journal of Information Systems*, Vol. 17 No. 1, pp. 4-11, doi: 10.1057/palgrave.ejis.3000726.

Eastin, M.S. and LaRose, R. (2000), "Internet self-efficacy and the psychology of the digital divide", *Journal of Computer-Mediated Communication*, Vol. 6 No. 1, JCMC611, doi: 10.1111/j.1083-6101.2000.tb00110.x.

Engelberger, J.F. (2012), *Robotics in Practice: Management and Applications of Industrial Robots*, Springer Science and Business Media, London.

Fan, A., Wu, L., Miao, L. and Mattila, A.S. (2020), "When does technology anthropomorphism help alleviate customer dissatisfaction after a service failure? – The moderating role of consumer technology self-efficacy and interdependent self-construal", *Journal of Hospitality Marketing and Management*, Vol. 29 No. 3, pp. 269-290, doi: 10.1080/19368623.2019.1639095.

Fang, X., Chan, S., Brzezinski, J. and Xu, S. (2005), "Moderating effects of task type on wireless technology acceptance", *Journal of Management Information Systems*, Vol. 22 No. 3, pp. 123-157, doi: 10.2753/mis0742-1222220305.

Fernandes, T. and Oliveira, E. (2021), "Understanding consumers' acceptance of automated technologies in service encounters: drivers of digital voice assistants adoption", *Journal of Business Research*, Vol. 122, pp. 180-191, doi: 10.1016/j.jbusres.2020.08.058.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50, doi: 10.1177/002224378101800104.

Fu, S., Zheng, X. and Wong, I.A. (2022), "The perils of technology: the robot usage resistance model", *International Journal of Hospitality Management*, Vol. 102, 103174, doi: 10.1016/j.ijhm.2022.103174.

Fuentes-Moraleda, L., Díaz-Pérez, P., Orea-Giner, A., Muñoz-Mazón, A. and Villacé-Molinero, T. (2020), "Interaction between hotel service robots and humans: a hotel-specific Service Robot Acceptance Model (sRAM)", *Tourism Management Perspectives*, Vol. 36, 100751, doi: 10.1016/j.tmp.2020.100751.

Fusté-Forné, F. and Ivanov, S. (2021), "Robots in service experiences: negotiating food tourism in pandemic futures", *Journal of Tourism Future*, Vol. 7 No. 3, pp. 1-8, doi: 10.1108/JTF-10-2020-0179.

Go, H., Kang, M. and Suh, S.C. (2020), "Machine learning of robots in tourism and hospitality: interactive technology acceptance model (iTAM) – cutting edge", *Tourism Review*, Vol. 75 No. 4, pp. 625-636, doi: 10.1108/TR-02-2019-0062.

Gretzel, U. and Murphy, J. (2019), "Making sense of robots -consumer discourse on robots in tourism and hospitality service settings", in Ivanov, S. and Webster, C. (Eds), *Robots, Artificial Intelligence and Service Automation in Travel, Tourism and Hospitality*, Emerald, Bingley, pp. 93-104, doi: 10.1108/978-1-78756-687-320191005.

Guenzi, P. and Pelloni, O. (2004), "The impact of interpersonal relationships on customer satisfaction and loyalty to the service provider", *International Journal of Service Industry Management*, Vol. 15 No. 4, pp. 365-384, doi: 10.1108/09564230410552059.

Gursoy, D., Chi, O.H., Lu, L. and Nunkoo, R. (2019), "Consumers acceptance of artificially intelligent (AI) device use in service delivery", *International Journal of Information Management*, Vol. 49, pp. 157-169, doi: 10.1016/j.ijinfomgt.2019.03.008.

Hair, J.F., Sarstedt, M., Pieper, T.M. and Ringle, C.M. (2012), "The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications", *Long Range Planning*, Vol. 45 Nos 5-6, pp. 320-340, doi: 10.1016/j.lrp.2012.09.008.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2013), "Partial least squares structural equation modeling: rigorous applications, better results and higher acceptance", *Long Range Planning*, Vol. 46 Nos 1-2, pp. 1-12, doi: 10.1016/j.lrp.2013.01.001.

Hasan, B. (2006), "Delineating the effects of general and system-specific computer self-efficacy beliefs on IS acceptance", *Information and Management*, Vol. 43 No. 5, pp. 565-571, doi: 10.1016/j.im.2005.11.005.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), "A new criterion for assessing discriminant validity in variance-based structural equation modelling", *Journal of The Academy of Marketing Science*, Vol. 43 No. 1, pp. 115-135, doi: 10.1007/s11747-014-0403-8.

Hotel Technology News (2019), "FlyZoo hotel: the hotel of the future or just more technology hype?", Published 29.03.2019. Downloaded 17.05.2019, available at: https://hoteltechnologynews.com/2019/03/flyzoo-hotel-the-hotel-of-the-future-or-just-more-technology-hype/

Hsu, M.-H. and Chiu, C.-M. (2004), "Internet self-efficacy and electronic service acceptance", *Decision Support Systems*, Vol. 38 No. 3, pp. 369-381, doi: 10.1016/j.dss.2003.08.001.

Huang, T. (2022), "What affects the acceptance and use of hotel service robots by elderly customers?", *Sustainability*, Vol. 14 No. 23, 16102, doi: 10.3390/su142316102.

Huang, M.-H. and Rust, R.T. (2018), "Artificial intelligence in service", *Journal of Service Research*, Vol. 21 No. 2, pp. 155-172, doi: 10.1177/1094670517752459.

Huang, Y.-C., Chang, L.L., Yu, C.-P. and Chen, J. (2019), "Examining an extended technology acceptance model with experience construct on hotel consumers' adoption of mobile applications", *Journal of Hospitality Marketing and Management*, Vol. 28 No. 8, pp. 957-980, doi: 10.1080/19368623.2019.1580172.

Huang, D., Chen, Q., Huang, J., Kong, S. and Li, Z. (2021), "Customer-robot interactions: understanding customer experience with service robots", *International Journal of Hospitality Management*, Vol. 99, 103078, doi:10.1016/j.ijhm.2021.103078.

Hwang, J. and Seo, S. (2016), "A critical review of research on customer experience management: theoretical, methodological and cultural perspectives", *International Journal of Contemporary Hospitality Management*, Vol. 28 No. 10, pp. 2218-2246, doi: 10.1108/IJCHM-04-2015-0192.

Ivanov, S. and Webster, C. (2019), "Economic fundamentals of the use of robots, artificial intelligence and service automation in travel", in Ivanov, S. and Webster, C. (Eds), *Robots, Artificial Intelligence and Service Automation in Travel, Tourism and Hospitality*, Emerald, pp. 39-55, doi: 10.1108/978-1-78756-687-320191002.

Ivanov, S.H., Webster, C. and Berezina, K. (2017), "Adoption of robots and service automation by tourism and hospitality companies", *Revista Turismo and Desenvolvimento*, Vol. 27 No. 28, pp. 1501-1517, available at: https://ssrn.com/abstract=2964308

Ivanov, S., Gretzel, U., Berezina, K., Sigala, M. and Webster, C. (2019), "Progress on robotics in hospitality and tourism: a review of the literature", *Journal of Hospitality and Tourism Technology*, Vol. 10 No. 4, pp. 489-521, doi: 10.1108/JHTT-08-2018-0087.

Kang, Y., Choi, N. and Kim, S. (2021), "Searching for new model of digital informatics for human–computer interaction: testing the institution-based technology acceptance model (ITAM)", *International Journal of Environmental Research and Public Health*, Vol. 18 No. 11, p. 5593, doi: 10.3390/ijerph18115593.

Kätsyri, J., Förger, K., Mäkäräinen, M. and Takala, T. (2015), "A review of empirical evidence on different uncanny valley hypotheses: support for perceptual mismatch as one road to the valley of eeriness", *Frontiers in Psychology*, Vol. 6, p. 390, doi: 10.3389/fpsyg.2015.00390.

Kharub, I., Lwin, M., Khan, A. and Mubin, O. (2021), "Perceived service quality in HRI: applying the SERVBOT framework", *Frontiers in Robotics and AI*, Vol. 8, 746674, doi: 10.3389/frobt.2021.746674.

Kipnis, E., McLeay, F., Grimes, A., De Saille, S. and Potter, S. (2022), "Service robots in long-term care: a consumer-centric view", *Journal of Service Research*, Vol. 25 No. 4, pp. 667-685, doi: 10.1177/109467052211108.

Kock, N. (2011), "Using WarpPLS in e-collaboration studies: descriptive statistics, settings, and key analysis results", *International Journal of E-Collaboration (IJeC)*, Vol. 7 No. 2, pp. 1-18.

Kock, N. (2014), *Stable P Value Calculation Methods in PLS-SEM*, ScriptWarp Systems, Laredo, TX, pp. 1-15.

Kock, N. (2015), "Common method bias in PLS-SEM: a full collinearity assessment approach", *International Journal of E-Collaboration (IJeC)*, Vol. 11 No. 4, pp. 1-10, doi: 10.4018/ijec.2015100101.

Kock, N. (2016), "Hypothesis testing with confidence intervals and P values in PLS-SEM", *International Journal of E-Collaboration (IJeC)*, Vol. 12 No. 3, pp. 1-6, doi: 10.4018/ijec.2016070101.

Kulviwat, S., Bruner II, G.C., Kumar, A., Nasco, S.A. and Clark, T. (2007), "Toward a unified theory of consumer acceptance technology", *Psychology and Marketing*, Vol. 24 No. 12, pp. 1059-1084, doi: 10.1002/mar.20196.

Kumar, V., Rajan, B., Venkatesan, R. and Lecinski, J. (2019), "Understanding the role of artificial intelligence in personalized engagement marketing", *California Management Review*, Vol. 61 No. 4, pp. 135-155, doi: 10.1177/0008125619859317.

Leung, R. (2019), "Smart hospitality: Taiwan hotel stakeholder perspectives", *Tourism Review*, Vol. 74 No. 1, pp. 50-62, doi: 10.1108/tr-09-2017-0149.

Leung, R. (2022), "Konnichiwa, Mr. Robot: a direct observation of hotel visitors' attitudes and anxiety regarding service robots", *International Hospitality Review*, Vol. 38 No. 1, pp. 11-27, doi: 10.1108/IHR-08-2021-0058.

Lin, Y.I. and Mattila, S.A. (2021), "The value of service robots from the hotel guest's perspective: a mixed-method approach", *International Journal of Hospitality Management*, Vol. 94, 102876, doi: 10.1016/j.ijhm.2021.102876.

Liu, D., Li, Q. and Han, S. (2022), "Using extended technology acceptance model to assess the adopt intention of a proposed IoT-based health management tool", *Sensors 2022*, Vol. 22 No. 16, p. 6092, doi: 10.3390/s22166092.

Lu, L., Cai, R. and Gursoy, D. (2019), "Developing and validating a service robot integration willingness scale", *International Journal of Hospitality Management*, Vol. 80, pp. 36-51, doi: 10.1016/j.ijhm.2019.01.005.

McFarland, D. and Hamilton, D. (2006), "Adding contextual specificity to the technology acceptance model", *Computers in Human Behavior*, Vol. 22 No. 3, pp. 427-447, doi: 10.1016/j.chb.2004.09.009.

McLean, G. and Osei-Frimpong, K. (2019), "Hey Alexa.examine the variables influencing the use of artificial intelligent in-home voice assistants", *Computers in Human Behavior*, Vol. 99, pp. 28-37, doi: 10.1016/j.chb.2019.05.009.

McLeay, F., Osburg, V.-S., Yoganathan, V. and Patterson, A. (2021), "Replaced by a robot: service implications in the age of the machine", *Journal of Service Research*, Vol. 24 No. 1, pp. 104-121, doi: 10.1177/1094670520933354.

Mende, M., Scott, M., van Doorn, J., Grewal, D. and Shanks, I. (2019), "Service robots rising: how humanoid robots influence service experiences and elicit compensatory consumer responses", *Journal of Marketing Research*, Vol. 56 No. 4, pp. 535-556, doi: 10.1177/0022243718822827.

Müller, V.C. (2020), *Ethics of Artificial Intelligence and Robotics*, The Stanford Encyclopedia of Philosophy, April 30, available at: https://plato.stanford.edu/entries/ethics-ai/

Najberg, A. (2018), "Alibaba to launch new service robot for hotels", Published (Alizila News from Alibaba Group) 21.09.2018. Downloaded 12.12.2018, available at: https://www.alizila.com/alibaba-unveils-new-service-robot-for-hotels/

Pagani, M. (2004), "Determinants of adoption of third generation mobile multimedia services", *Journal of Interactive Marketing*, Vol. 18 No. 3, pp. 46-59, doi: 10.1002/dir.20011.

Pinillos, R., Marcos, S., Feliz, R., Zalama, E. and Gómez-García-Bermejo, J. (2016), "Long-term assessment of a service robot in a hotel environment", *Robotics and Autonomous Systems*, Vol. 79, pp. 40-57, doi: 10.1016/j.robot.2016.01.014.

Podsakoff, P.M. and Organ, D.W. (1986), "Self-reports in organizational research: problems and prospects", *Journal of Management*, Vol. 12 No. 4, pp. 531-544, doi: 10.1177/014920638601200408.

Richter, N.F., Hauff, S., Kolev, A.E. and Schubring, S. (2023), "Dataset on an extended technology acceptance model: a combined application of PLS-SEM and NCA", *Data in Brief*, Vol. 48, 109190, doi: 10.1016/j.dib.2023.109190.

Rondan-Cataluña, F.J., Arenas-Gaitán, J. and Ramírez-Correa, P.E. (2015), "A comparison of the different versions of popular technology acceptance models", *Kybernetes*, Vol. 44 No. 5, pp. 788-805, doi: 10.1108/K-09-2014-0184.

Saber Chtourou, M. and Souiden, N. (2010), "Rethinking the TAM model: time to consider fun", *Journal of Consumer Marketing*, Vol. 27 No. 4, pp. 336-344, doi: 10.1108/07363761011052378.

Sánchez-Prieto, J.C., Olmos-Migueláñez, S. and García-Peñalvo, F.J. (2017), "@MLearning and pre-service teachers: an assessment of the behavioral intention using an expanded TAM model", *Computers in Human Behavior*, Vol. 72, pp. 644-654, doi: 10.1016/j.chb.2016.09.061.

Sheth, J.N., Newman, B.I. and Gross, B.L. (1991), "Why we buy what we buy: a theory of consumption values", *Journal of Business Research*, Vol. 22 No. 2, pp. 159-170, doi: 10.1016/0148-2963(91)90050-8.

Tanrikulu, C. (2021), "Theory of consumption values in consumer behaviour research: a review and future research agenda", *International Journal of Consumer Studies*, Vol. 45 No. 6, pp. 1176-1197, doi: 10.1111/ijcs.12687.

Teo, T. (2009), "Modelling technology acceptance in education: a study of pre-service teachers", *Computers and Education*, Vol. 52 No. 2, pp. 302-312, doi: 10.1016/j.compedu.2008.08.006.

Tung, V.W.S. and Au, N. (2018), "Exploring customer experiences with robotics in hospitality", *International Journal of Contemporary Hospitality Management*, Vol. 30 No. 7, pp. 2680-2697, doi: 10.1108/ijchm-06-2017-0322.

Tung, V.W.S. and Law, R. (2017), "The potential for tourism and hospitality experience research in human-robot interactions", *International Journal of Contemporary Hospitality Management*, Vol. 29 No. 10, pp. 2498-2513, doi: 10.1108/IJCHM-09-2016-0520.

Tuomi, A., Tussyadiah, I.P. and Stienmetz, J. (2020a), "Applications and implications of service robots in hospitality", *Cornell Hospitality Quarterly*, Vol. 62 No. 2, pp. 232-247, doi: 10.1177/1938965520923961.

Tuomi, A., Tussyadiah, I. and Stienmetz, J. (2020b), "Service robots and the changing roles of employees in restaurants: a cross cultural study", *E-review of Tourism Research*, Vol. 17 No. 5, Downloaded: 05.09.2022, available at: https://ertr-ojs-tamu.tdl.org/ertr/article/view/550

Turja, T., Rantanen, T. and Oksanen, A. (2019), "Robot use self-efficacy in healthcare work (RUSH): development and validation of a new measure", *AI and Society*, Vol. 34 No. 1, pp. 137-143, doi: 10.1007/s00146-017-0751-2.

Tussyadiah, I. (2020), "A review of research into automation in tourism: launching the annals of tourism research curated collection on artificial intelligence and robotics in tourism", *Annals of Tourism Research*, Vol. 81, 102883, doi: 10.1016/j.annals.2020.102883.

Tussyadiah, I. and Park, S. (2018), "Consumer evaluation of hotel service robots", in Stangl, B. and Pesonen, J. (Eds), *Information and Communication Technologies in Tourism 2018*, Springer, pp. 308-320.

van Doorn, J., Mende, M., Noble, S.M., Hulland, J., Ostrom, A.L., Grewal, D. and Petersen, J.A. (2017), "Domo Arigato Mr. Roboto: emergence of automated social presence in organizational frontlines and customers' service experiences", *Journal of Service Research*, Vol. 20 No. 1, pp. 43-58, doi: 10.1177/1094670516679272.

Venkatesh, V. and Bala, H. (2008), "Technology acceptance model 3 and a research agenda on interventions", *Decision Sciences*, Vol. 39 No. 2, pp. 273-315, doi: 10.1111/j.1540-5915.2008.00192.x.

Venkatesh, V. and Davis, F.D. (2000), "A theoretical extension of the technology acceptance model: four longitudinal field studies", *Management Science*, Vol. 46 No. 2, pp. 186-204, doi: 10.1287/mnsc.46.2.186.11926.

Venkatesh, V., Speier, C. and Morris, M.G. (2002), "User acceptance enablers in individual decision making about technology: toward an integrated model", *Decision Science*, Vol. 33 No. 2, pp. 297-316, doi: 10.1111/j.1540-5915.2002.tb01646.x.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478, doi: 10.2307/30036540.

Venkatesh, V., Thong, Y.L.J. and Xu, X. (2012), "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology", *MIS Quarterly*, Vol. 36 No. 1, pp. 157-178, doi: 10.2307/41410412.

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A. and Trichina, E. (2021), "Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review", *The International Journal of Human Resource Management*, Vol. 33 No. 6, pp. 1-30, doi: 10.1080/09585192.2020.1871398.

Wang, C., Ahmad, S.F., Bani Ahmad Ayassrah, A.Y.A., Awwad, E.M., Irshad, M., Ali, Y.A., Al-Razgan, M., Khan, Y. and Han, H. (2023), "An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce", *Heliyon*, Vol. 9 No. 8, e18349, doi: 10.1016/j.heliyon.2023.e18349.

Weiss, A., Bernhaupt, R., Lankes, M. and Tscheligi, M. (2009), "The USUS evaluation framework for human-robot interaction", *AISB2009: Proceedings of the Symposium on New Frontiers in Human-Robot Interaction*, Vol. 4, pp. 11-26, doi: 10.1186/1750-1326-4-11.

Wetzels, M., Odekerken-Schröder, G. and Van Oppen, C. (2009), "Using PLS path modeling for assessing hierarchical construct models: guidelines and empirical illustration", *MIS Quarterly*, Vol. 33 No. 1, pp. 177-195, doi: 10.2307/20650284.

Wilson, H.J. and Daugherty, P.R. (2018), "Collaborative intelligence: humans and AI are joining forces", *Harvard Business Review*, Vol. 96 No. 4, pp. 114-123.

Wirtz, J., Patterson, P.G., Kunz, W.H., Gruber, T., Lu, V.N., Paluch, S. and Martins, A. (2018), "Brave new world: service robots in the frontline", *Journal of Service Management*, Vol. 29 No. 5, pp. 907-931, doi: 10.1108/JOSM-04-2018-0119.

Yan, H., Ang, M.H. and Poo, A.N. (2014), "A survey on perception methods for human–robot interaction in social robots", *International Journal of Social Robotics*, Vol. 6 No. 1, pp. 85-119, doi: 10.1007/s12369-013-0199-6.

Zhong, L., Sun, S., Law, R. and Zhang, X. (2020), "Impact of robot hotel service on consumers' purchase intention: a control experiment", *Asia Pacific Journal of Tourism Research*, Vol. 25 No. 7, pp. 780-798, doi: 10.1080/10941665.2020.1726421.

Zhong, L., Zhang, X., Rong, J., Chan, H.K., Xiao, J. and Kong, H. (2021), "Construction and empirical research on acceptance model of service robots applied in hotel industry", *Industrial Management and Data Systems*, Vol. 121 No. 6, pp. 1325-1352, doi: 10.1108/IMDS-11-2019-0603.

Appendix

Table A1. Control variable model

	SE	PI	PU	PE	RE	Age	Gender	Nationality
Path coefficients								
SE						−0.247	−0.115	−0.080
PI	0.563					−0.117	−0.040	−0.021
PU	0.258	0.535				−0.116	0.056	0.051
PE	0.181	0.728				−0.056	0.047	−0.053
RE		0.421	0.136	0.009		−0.184	0.044	0.057
P-values								
SE						<0.001	0.040	0.112
PI	<0.001					0.038	0.276	0.378
PU	<0.001	<0.001				0.038	0.199	0.220
PE	0.003	<0.001				0.201	0.242	0.212
RE		<0.001	0.019	0.447		0.002	0.255	0.194

Source(s): Authors work

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