International Journal of Hospitality Management 114 (2023) 103587

Contents lists available at ScienceDirect

International Journal of Hospitality Management

journal homepage: www.elsevier.com/locate/ijhm

Role of trust in customer attitude and behaviour formation towards social service robots

Valentina Della Corte [a,*], Fabiana Sepe [a], Dogan Gursoy [b,c], Anna Prisco [a]

[a] University of Naples Federico II, Via Cintia, 21- 80126, Naples, Italy
[b] Washington State University, Pullman, WA 99164-4736, USA
[c] School of Tourism and Hospitality, University of Johannesburg, Johannesburg, South Africa

ARTICLE INFO

Keywords:
Artificial intelligence
Social service robots
Anthropomorphism
Trust in social service robots
Service delivery
Hedonic services
Functional services
Technology acceptance

ABSTRACT

This research proposes a model that identifies the antecedents of customers' attitudes and behaviours towards the utilization of artificially intelligent (AI) social service robots in hospitality and tourism service delivery. The model highlights the importance of trust and its determinants on customers' attitudes and behaviours towards social service robots. The proposed model and the hypotheses are tested utilizing data collected from the users of two distinctly different hospitality and tourism services. Data were analysed adopting a PLS-SEM approach. Results indicate that the level of acceptance of the use of social robots in service delivery is determined by a multistage process, in which trust perceptions play critical roles. Heuristic (i.e., hedonic motivation) and the individual (i.e., innovativeness) factors positively influence trust in social robots during service delivery. Findings, however, suggest significant differences in different service contexts: anthropomorphism has no effect on trust construct and effort expectancy does not influence positive emotion in hedonic service contexts while these relationships are significant in functional service contexts. Practical and theoretical implications of the findings are discussed.

1. Introduction

Artificially intelligent social robots are artificially intelligent systems that can be programmed to perform different tasks in various contexts, including service delivery. While artificial intelligence technology has been around for a few decades, companies have recently started utilizing social robots in delivering services. However, its use has been increasing widely in the most recent times since artificial intelligent technology goes beyond automation by empowering robots to have analytical, mechanical, intuitive, and empathetic intelligence (Huang and Rust, 2018). Furthermore, COVID-19 pandemic (Chuah et al., 2022), and great resignation and quiet quitting trends among employees have been accelerating the integration of social robots into service encounters (Söderlund, 2021) such as restaurants (Lu et al., 2021), hotels, airlines (Chi et al., 2022), and tourism destinations (Hou et al., 2021). Adoption of artificially intelligent devices to enhance customer experiences is also gaining traction since they can offer a range of services such as increased personalization to tailored recommendations.

Several scholars have examined a number of aspects of social robot use in service delivery. Those works investigated robotization of hospitality services (Khoa et al., 2022; Seyitoğlu and Ivanov, 2023), customer attitudes and behaviours towards the utilization of social robots (Lu et al., 2019; Ivanov et al., 2018), impacts on employees' turnover intentions and awareness of robotics (Li et al., 2019), customer evaluation of social robots (Lv et al., 2022), nudge effect of robots on tourist behaviors (Tussyadiah et al., 2020), customer willingness to pay for services delivered by robots (Ivanov and Webster, 2021), etc.

Even though the utilization of social robots in delivering services can benefit both providers and customers (Saydam et al., 2022), past research demonstrates that not all customers are willing to consume services delivered by social robots (Chi et al., 2020; van Esch et al., 2022). While some scholars argue that the adoption of social robots may improve customer perception of service performance and quality (Chiang and Trimi, 2020), leading to higher willingness to adopt these technologies in hospitality contexts, other suggest that the lack of social interaction may lead customers to perceive a sense of loneliness (Odekerken-Schröder et al., 2020), resulting in an objection toward the use of these technologies. Artificially intelligent devices' perceived intelligence and their level of anthropomorphism may also influence customers' behavioural intentions to use these technologies (Zhang

* Corresponding author.
E-mail address: valentina.dellacorte@unina.it (V. Della Corte).

https://doi.org/10.1016/j.ijhm.2023.103587
Received 10 March 2023; Received in revised form 25 July 2023; Accepted 19 August 2023
Available online 27 August 2023

et al., 2021). Given that the research on understanding customers' attitudes and behaviours towards the utilization of social robots in delivering hospitality and tourism services is still relatively new and developing, more studies are still needed to advance our understanding of customer attitudes and behaviours towards the use of social robots in service delivery and its antecedents (Tung and Law, 2017; Park, 2020; Kim et al., 2022). Thus, this study aims to advance the social robot adoption literature by proposing and testing a theoretical model that identifies and examines the most crucial factors that can affect customer attitudes and behaviours towards the use of social robots in hospitality and tourism service delivery.

While previous studies proposed conceptual frameworks (Gursoy et al., 2019) to investigate customer attitudes and behaviours towards the use of social robots in hospitality and tourism service delivery, customer trust in a social service robot's ability to deliver a satisfactory service experience has not received much attention even though trust is a critical factor that can shape customers' attitudes and behaviours. Because social service robots are capable of having verbal interactions and making decisions since they have relatively high levels of intelligence (Thrun, 2004), it is necessary to examine the influence of trust in those devices on customers' attitudes and behaviours, and the determinants of that trust. Thus, this study integrates customer trust into the decision-making mechanism customers use to determine their attitudes and behaviours towards social robot use in the services context.

Since the level of trust in social robots' abilities to deliver the expected services can influence customers' attitudes and behaviours towards social robots (Chi et al., 2023), this study identifies most critical determinants of trust and investigates their effects on customers' willingness to accept the use of social robots in service delivery. Understanding the antecedents of trust is crucial for identifying the possible interventions to alleviate social and technical complexities, which can enable service providers to enhance users' experiences (Söllner and Pavlou, 2016; Della Corte, 2020). This study argues that both individual and heuristic factors serve as critical antecedents of trust in social service robots. Consumers' trust perceptions, in turn, influence systemic factors, positive emotions and the level of acceptance of the utilization of social robots in delivering services. Since the service context and expectations can influence customer willingness to interact with social robots, this research examines the antecedents of customers' acceptance of the utilization of social robots in two different service contexts: hotels and airports.

Findings of this study will make important novel contributions to the human-robot interaction literature. This study extends the Artificially Intelligent Device Use Acceptance (AIDUA) theory by exploring whether trust in social robots' abilities influences systemic factors and, in turn, emotions. Findings will help us clarify the role of trust in social robots' abilities on the overall quality of human-robot interaction experiences in the hospitality and tourism service delivery. Furthermore, this study introduces new insights and perspectives that enhance our understanding of how individuals perceive artificially intelligent social service robot use in service delivery. This study also provides a response to Belanche et al.'s (2020) call for a conceptual framework that can be used by both researchers and industry practitioners for successful implementation of artificially intelligent social robots in service delivery. Thus, this study makes important contributions to the artificially intelligent social robot acceptance and human-robot interaction literature by advancing the artificially intelligent social robot acceptance framework. Findings of this study will provide theoretical and practical insights that serve as basis for further research and development in the area of human-robot interaction.

Findings will also further enhance our understanding of the process that determines customers' attitudes and behaviours towards social robots' utilization in delivering hospitality and tourism services, and the critical role of trust in this process by testing the proposed model in two different service contexts: hotels and airports. The decision to test the conceptual model in two different service contexts derives from the need to provide methodological rigor and enhance the validity of the proposed model. Furthermore, findings from testing the conceptual model in two different contexts will enable us to gain a more exhaustive knowledge of all aspects characterizing a given phenomenon. Airports and hotels are very different service contexts, since the first one provides more functional services that focus on convenience-driven automation (high-tech), while the hotel context provides more guest–employee interaction with more hedonic components occurring in the service experience (high-touch) (Zeng et al., 2020; Davari et al., 2022). Findings will help us gain a more comprehensive understating of when and in what service context the use of artificially intelligent social service robots use in service delivery is appropriate since customers in different service contexts have distinct goals and expectations for their service encounters (Schepers et al., 2022). Thus, findings will contribute valuable new insights to the existing literature, which has predominantly focused on the anthropomorphism of robots and its boundary conditions (Tung and Au, 2018).

2. Literature review

Several theoretical frameworks have been adopted to predict and explain new information and communication technologies (ICT) acceptance by users. Among them, the most frequently used ones are the TAM (Technology Acceptance Model) (Venkatesh and Davis, 2000), and the UTAUT (Unified Theory of Acceptance and Use of Technology) model (Venkatesh et al., 2003; Escobar-Rodríguez & Carvajal-Trujillo, 2014). Most works that examined artificial intelligent devices also integrated decision-making models including the TRA (Theory of Reasoned Action) and the TPB (Theory of Planned Behaviour) into their studies due to the differences in evaluations of and expectations from social robots and functional technologies (Huang and Rust, 2018). However, as argued by Mehta et al. (2022), findings of studies that utilized TRA or UTAUT conceptual frameworks for studying individuals' attitudes and behaviors towards artificially intelligent devices appear to be fragmented and not exhaustive enough.

Given that artificially intelligent technologies have unique characteristics (i.e., humanlike mind, intelligence, etc.) that are quite different from traditional functional technologies, the long-established technology acceptance theories and models are not appropriate to study customers' attitudes toward the artificially intelligent device utilization in service delivery. To address this issue, Gursoy et al. (2019) introduced the AIDUA framework, which argues that six factors, namely, anthropomorphism, hedonic motivations, social influence, effort and performance expectancy, and emotions determine customers' attitudes and behaviours towards social robots' utilization in delivering services. Unlike the above-mentioned theories and models that study the drivers of unintelligent technology acceptance, the AIDUA framework was specifically developed to investigate artificially intelligent device use in service delivery. As argued by Filieri et al. (2022), emotion plays an important role in the context of social robot acceptance. Thus, the AIDUA framework emphasizes the impact of emotions on users' intentions to accept the use of artificially intelligent service devices, suggesting that behavioral intention towards artificially intelligent devices is mainly driven by individuals' emotions (Gursoy et al., 2019).

The AIDUA model, building on Cognitive Appraisal Theory (Lazarus, 1991) and Cognitive Dissonance Theory (Festinger, 1962), explores the multi-step process used by customers to determine their willingness to accept the use of social robots in different service delivery contexts. As reported by Gursoy et al. (2019), the AIDUA model can be used to explain customers' willingness to accept the use of AI devices or to refuse AI devices usage during service encounters. Other studies such as Lin et al. (2020) have confirmed that the AIDUA model provides a theoretically and conceptually sound framework for studying the process that leads to customers' acceptance or objection to the artificially intelligent service devices' usage. Several studies have utilized the AIDUA model as the conceptual framework in different contexts such as in airline and hospitality services (Chi et al., 2020, 2022), full-service and limited-service hotels (Lin et al., 2019), and autonomous vehicles (Ribeiro et al., 2021). While the AIDUA was utilized as the underlying conceptual framework in several studies that examined artificially intelligent device utilization in various service delivery contexts (Lin et al., 2019), it fails to consider the vital role played by trust in social robots' acceptance by consumers. As argued by traditional theories in human behaviors (Spooncer, 1992), individuals' behavioral intentions are likely to be driven by not only emotions but also cognitive beliefs, such as trust. Furthermore, recent studies suggest that trust is a significant antecedent of technology acceptance in artificial intelligence context (Park, 2020). As suggested by the Social Exchange Theory (Homans, 1958), trust plays a critical role in social interactions, which can influence customers' perception of service quality and their service experiences. Thus, this study extends the underlying mechanism consumers utilize to determine their acceptance of the use of social robots in service delivery by proposing a conceptual model that integrates trust and its antecedents as critical determinants.

3. Hypothesis development

3.1. Heuristic factors

3.1.1. Social influence

Social influence refers to the extent to which the social context can influence consumer perception of the benefits of utilizing a specific technology (Venkatesh et al., 2012). Since attitudes of social group members toward the usage of social robots can have significant impacts on individuals' attitudes and behaviors (Maruping et al., 2017), individuals are likely to exhibit attitudes and behaviors that are compatible with group norms based on their assessment of whether their social groups (e.g., family, co-workers, friends, and social networks) consider the use of social robots as acceptable or not. Furthermore, social influence plays a critical role in determining the level of an individual's trust towards a particular service (Baabdullah, 2018). When people find that their peers (do not) prefer and (do not) have positive attitudes toward the use of a technology such as social robots, they consequently (do not) develop trust towards that technology's ability to meet their expectations. Based on the above considerations, we argue that:

H1. : Social influence significantly influences customers' trust in social service robots.

3.1.2. Hedonic motivation

Hedonic motivation, in this study context, refers to perceived enjoyment, fun, and entertainment customers can experience while utilizing artificially intelligent devices (Lee et al., 2021). As highlighted in prior research, if an individual perceives that using a social robot is likely to be enjoyable and fun, his/her level of trust to adopt this technology is likely to be positive (Vitezić and Perić, 2021). Thus, this study proposes that:

H2. : Hedonic motivation increases customers' trust in social service robots.

3.1.3. Anthropomorphism

Anthropomorphism refers to the level of perceived level of human-likeness, such as self-consciousness, human appearance, and emotions (Kim and McGill, 2018; Gursoy et al., 2019; Natarajan & Gombolay, 2020). Anthropomorphic service robots possess human characteristics and emulate human behaviours (Yang et al., 2022). Furhat is a symbol of a humanoid robot that can detect and mimic human emotions. Because of its ability to interact with humans, Furhat has been utilized in several service contexts including airports, train stations, hotels, etc. (Gonzalez-Aguirre et al., 2021).

Effects of artificial intelligent devices' level of anthropomorphism on humans' attitudes and behaviors towards those artificial intelligent devices have been investigated extensively in various research contexts (Pelau et al., 2021; Soderlund et al., 2021). However, previous studies have reported contradictory findings. While some studies have highlighted negative relationships between perceived anthropomorphism and users' attitudes (Lu et al., 2019), others reported positive effects (Han and Yang, 2018; Zhang et al., 2021). In the context of human-robot interaction, Lu et al. (2019) study on customers' willingness to use a robotic device in a hotel, the hotel guests' willingness was negatively influenced by the robot's human-like characteristics. On the other hand, a study conducted by Zhang et al. (2020) reported that more human-like characteristics were linked to users' positive emotional feedback. These contradictory results demonstrate the need for further examination of the role of anthropomorphism on acceptance behaviours. These contradictory findings might be explained by the fact that most of those studies have mainly focused on anthropomorphistic features of social robots. However, as argued by Zlotowski et al. (2015), individuals' characteristics, such as motivations, social background, gender and age may also have significant impact on how those individuals view anthropomorphism of social robots, and thus, on their attitudes and behaviors towards those social robots.

While previous studies reported contradictory findings about the effects of perceived anthropomorphism on individuals' attitudes and behaviours towards the utilization of artificial intelligent devices in delivering services, anthropomorphism was found to be an important antecedent of trust (Liu and Tao, 2022; Liu et al., 2022). Qiu and Benbasat (2009) argued that when users interact with a more anthropomorphic software, their perceptions of social presence significantly increase. In this light, this work proposes that:

H3. : Anthropomorphism has a positive effect on customers' trust in social service robots.

To sum up, social influence, anthropomorphism, and hedonic motivation are key heuristic factors that play significant roles in shaping human behaviour and decision-making process. Recognizing the impact of these factors on trust might help us better understand how these cognitive biases shape consumer behaviour, influence user experiences, and drive both engagement and trust. The heuristic factors in the context of robotics often focus on psychological and cognitive aspects of human behavior and decision-making process, rather than the basic software and hardware functions of a robot. While perception, learning, autonomy, manipulation, and physical context are crucial aspects of robotics and human-robot interaction, they are typically considered as technical factors rather than as heuristic factors (Shi et al., 2021). These technical factors encompass the main capabilities and functionalities of a robot, such as its ability to sense and perceive the environment, learn from data and experiences, autonomously perform tasks, manipulate objects, and navigate physical contexts. Understanding these technical aspects is essential for designing and developing effective robotic systems. However, when discussing heuristic factors, the focus shifts towards exploring how humans perceive and interact with robots, how they make decisions regarding robots' use and acceptance, and how psychological biases and heuristics can influence these processes. As suggested by Belanche et al. (2020) and Flavián and Casaló (2021), a thorough understanding of consumers' attitudes and behaviors towards artificially intelligent social service robots requires investigation of not only the technical factors related to robot design issues but also the customer characteristics and service encounter features.

3.1.4. Individual factors

3.1.4.1. Perceived risk. Perceived service risk refers to customers' perception of possible losses due to failures during a service delivery (Fuchs and Reichel, 2011) and/or uncertainty related to the service quality (Yin et al., 2020). In most cases, if customers are not certain about the ability of a service provider to deliver quality in service provision, they are less likely to trust the provider and, thus, refuse to use and/or recommend the service. Studies that examined technology adoption have also reported negative relationships between the level of risk and the level of trust in different technology use contexts. These studies reported that when the risk and/or the uncertainty is high, consumers tend to have less trust in a specific technology's ability to meet their expectations (Lee et al., 2010). Especially, if individuals are not able to figure out the reasons behind the failure of a service delivered by a artificially intelligent social service robot, they may experience a sense of diminished authority or control over the situation, which may lower their level of trust in a social robot's ability to deliver satisfactory services. Thus, the following hypothesis has been formulated:

H4. : Perceived risk negatively influences customers' trust in social service robots.

3.1.4.2. Personal innovativeness. Innovativeness was first introduced by Agarwal and Prasad (1998) as a critical determinant of a user's willingness to try out any new information system. It relates to the ability of individuals to be open to new ideas and exploit them to find new solutions (Crawford & Di Benedetto, 2003). Innovative individuals tend to have higher trust in new technologies than their non-innovative counterparts. Thus, they would like to experiment with new products or services (San Martín and Herrero, 2012). According to the Diffusion of Innovation Theory (DOI), innovative individuals tend to be early adopters of new innovations compared to their non-innovative counterparts (López-Nicolás et al., 2008). Studies suggest that innovativeness, as a psychological and individual factor, can predict a consumer's intention to adopt a new technology (Zhang et al., 2017). Specifically, if an individual shows the traits of innovativeness and curiosity, he/she will be more likely to develop trust and be the first to try and adopt new innovations. Based on the preceding discussion, the following hypothesis is proposed:

H5. : Innovativeness positively influences customers' trust in social service robots.

3.1.4.3. Trust in Artificial Intelligence. Xu and Howard (2018) consider trust as a catalyst that influences human–robot interaction. Thus, rather than considering the issue of trust in individuals or companies, as has widely been utilized in previous hospitality studies, this study adopts a conceptualization of trust mainly related to service robots' abilities. The literature on trust views it as a belief characterized by the construction of some attributes of an object (Colquitt and Rodell, 2011). In this vein, trust is conceptualized as a cognitive belief formed based on interactions and cognitive/affective elements (Park, 2020). However, studies suggest that human-robot trust is different from human-automation trust (Natarajan and Gombolay, 2020). Artificially intelligent robots have a level of autonomy that allows them to adapt to unforeseen circumstances or events that were not explicitly programmed or predicted during their design. This sets them apart from automation, which is designed to strictly follow pre-established instructions, which makes the role of trust in human-robot interactions more complicated and challenging to understand.

When uncertainty is present, as in the case of emerging technologies such as social robots (Kim et al., 2020), the initial trust in social robots serves as a crucial determinant of primary assessment and a vital component of customer behaviours towards the utilization of social robots in delivering services. Furthermore, customers' level of trust in an artificial intelligent device plays a fundamental role in customers' assessment of both performance and effort expectancy (Ghazizadeh et al., 2012). Despite its importance, trust was not originally considered in the AIDUA framework. However, prior research (Ghazizadeh et al., 2012; Hengstler et al., 2016) argues that trust is a critical determinant of performance expectancy, especially for emerging technologies that might be considered as "disruptive". Trust also plays a vital role in reducing the negative effects of technical complications (Söllner et al., 2016). Thus, an elevated level of trust is likely to reduce the perceived effort needed to interact with social robots while increasing performance expectations (Lee and Song, 2013). In this light, the following hypothesis has been formulated:

H6. : Trust has a direct positive effect on performance expectancy of social service robots.

H7. : Trust has a direct negative effect on effort expectancy of social service robots.

3.1.4.4. Performance expectancy, effort expectancy and positive emotions. Several studies have considered emotions as one of the most crucial factors determining individuals' level of willingness to partake in human-robot interaction (Chuah and Yu, 2021; Desideri et al., 2019; Shank et al., 2019; Yu and Ngan, 2019) since emotions can determine the level of engagement and participation in co-creation of experiences (Tung and Au, 2018). In service robot context, emotions, viewed as positive feelings and mental states arising from interactions with service robots (Zhang et al., 2021), are derived from a specific appraisal of benefits and costs (Smith and Lazarus, 1993). As proposed by the cognitive appraisal theory, appraisal processes concern the cognitive elements, which determine individuals' assessment and beliefs based on their internal or external conditions (Lazarus, 1991). Thus, consumer emotional reactions are the outcome of their assessment of a stimulus, which further drives behavioural outcomes (Lazarus, 1991).

Previous studies argue that individuals form their emotions towards social robots based on their assessment of performance and effort expectancy during an interaction with a social robot (Gursoy et al., 2019). While performance expectancy refers to individuals' assessment of social robots' performance with reference to both service accuracy and consistency, effort expectancy, conceptually similar to perceived ease of use, refers to individuals' perception of mental efforts needed to interact with social robots. Other studies show that the higher the level of performance expectancy, higher the level of positive emotions toward the use of artificial intelligent devices, while higher levels of effort expectancy can have negative effects on individuals' opinion of these robotic agents.

H8. : Performance expectancy enhances individuals' positive emotions toward the social service robots.

H9. : Effort expectancy lowers individuals' positive emotions toward the social service robots.

According to Wirtz et al. (2018) consumer's attitudes and behaviours toward the use of social robots in delivering services depends on how well those social robots can satisfy utilitarian and emotional needs to gain role congruency. As argued by others, consumers' emotions formed based on their appraisal of performance and effort expectancy serves as a critical determinant of their attitudes and behaviours toward the utilization of those artificial intelligent devices in delivering services. Thus, grounded in the AIDUA framework, this study investigates the effect of the positive emotions on customers' attitudes and behaviours toward the utilization of artificial intelligent devices in delivering services (Gursoy et al., 2019).

H10. : Positive emotions have positive effects on attitudes and behaviours toward the utilization of artificial intelligent devices in delivering services.

Fig. 1 presents the conceptual model that is developed based on the proposed hypotheses.

4. Materials and methods

The model was tested in two service settings, a hotel and an airport for validating the findings and to improve external validity and

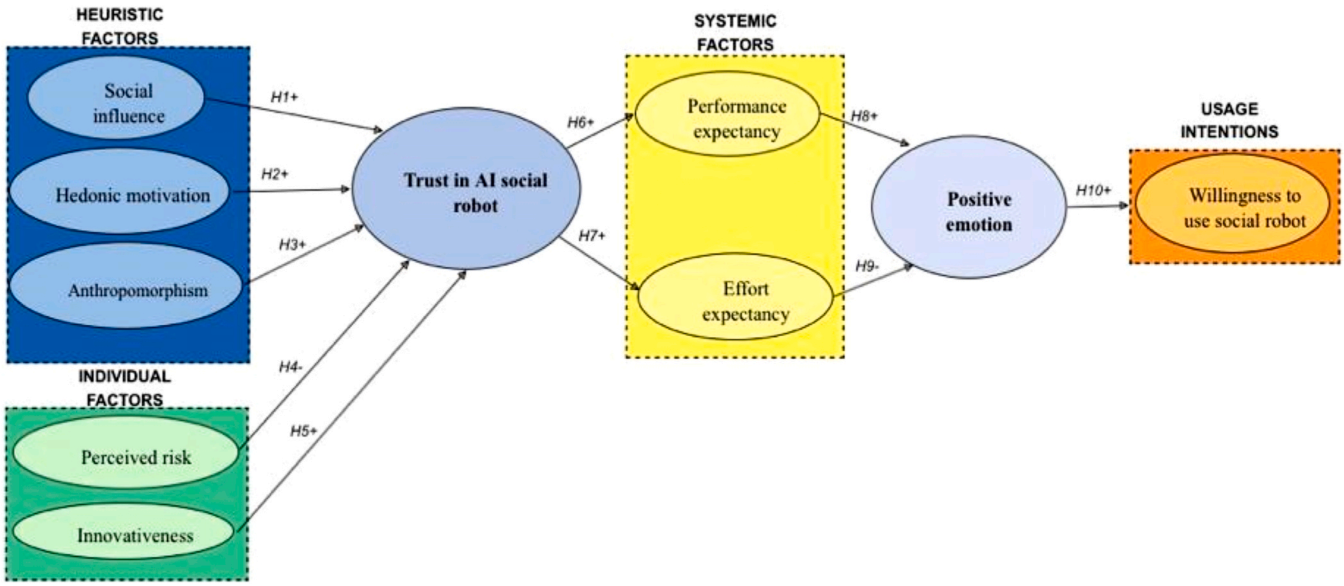

Fig. 1. the proposed model.

generalizability (Milman et al., 2020). This study used a hypothetical scenario method (Weber 1992). Scenario methods are used by other studies to examine consumer decision-making behaviour in emerging technology contexts (e.g., Ribeiro et al., 2022; Shi et al., 2021; Jun & Vogt 2013; Park & Jang 2013) because scenarios can ensure that contextual details that are needed for a realistic decision-making process are presented and consistent across respondents (Siponen & Vance 2010). Furthermore, this study adopted a prototypical humanoid robot (i.e., Furhat), since this social robot is designed to create a human-like setting during interaction (Wilcock and Jokinen, 2022).

The scenarios showed a situation where the person is asking for a restaurant recommendation from a social robot. Study 1 was focused on a hotel setting, while Study 2 was designed for an airport context. Data were collected utilizing an online survey. The first part included the consent form. The second part presented the purpose of the research and the definition of service robots and then asked respondents to read the assigned scenario that described a human-robots service encounter at a hotel or an airport (see the Appendix). Each scenario included a picture of Furhat social robot and a video that showed human-robot interaction in an airport or a hotel service context. Respondents were instructed to watch the video after reading the scenario to ensure that they understood the capabilities, mobility, and embodiment features of social robots. Manipulation check questions were also included in this section.

The third section included items that were used to measure each construct and five attention check questions. Each construct was measured utilizing items validated in literature. Perceived risk was measured with 5 items (Chi et al., 2021), innovativeness with 3 items (Hwang et al., 2020), social influence with 5 items and hedonic motivation with 4 items, both adapted from Lin et al. (2020), anthropomorphism with 4 items adapted from Gursoy et al. (2019), both performance and effort expectancy with 3 items (Chi et al., 2020), trust in social robots with 6 items (Park, 2020; Lippert and Davis, 2006), positive emotion with 5 items (Chi et al., 2020), willingness to use with 3 items (Shi et al., 2021). All items were measured on a 7-point Likert scale (1 =strongly disagree 7 =strongly agree).

The last section of the survey included demographic questions (such as age, gender, income, education level, occupation). Since the questionnaire was administered in Italian, it was translated into Italian using a translation back to translation procedures (Hair et al., 2019). Items from different constructs were intermixed to reduce retrieval bias (Podsakoff et al., 2003) Furthermore, in order to minimize social desirability bias the scope of the research and the survey was explained to respondents and contacts for further information were provided (Saunders et al., 2009).

First, a pilot study was carried out on 250 undergraduate students to test the validity and reliability of the questionnaire. Afterwards, data were collected utilizing Amazon's Mechanical Turk (MTurk) between March 10, 2022 and May 8, 2022. The final sample included 716 valid responses. (358 each in Studies 1 and 2).

Proposed model and the hypotheses were tested through the Partial Least Squares approach to Structural Equation Models (PLS-SEM) (Hair et al., 2014). PLS-SEM approach is used when the model is complex (direct, indirect, and moderation) and for non-normal data (Hair et al., 2019).

5. Results

5.1. Sample characteristics

The sample consisted of 40% male and 51% female, 9% of respondents did not report their gender. Around 32% of respondents were between the ages of 18–25, 28% were between the ages of 26–34, the 26% between the ages of 45–54, 10% were 55 years old or older. Income distribution of respondents was: 20% had income less than 10,000 euros, 30% between 10,000 and 29,999 euros, 25% between 30,000 and 59,999 euros, 15% between 60,000 and 89,999% and 10% between 90,000 and 129,000.

5.2. Measurement model

First, the convergent validity of the measurement model was assessed through examining the average variance extracted (AVE) scores, factor loadings, Cronbach's Alpha scores and composite reliability of each construct (Fornell and Bookstein 1982). As presented in Table 1, both in hotel and airport contexts all loadings were higher than 0.60, except for HM1 in hotel context (Henseler et al., 2009), each construct's Cronbach's alpha and composite reliability (CR) scores were higher than 0.70 and average variance extracted (AVE) score of each construct was higher than 0.50 (Hair et al., 2016).

Afterwards, the discriminant validity was checked using two criteria: Fornell-Larcker criterion and Heterotrait-Monotrait criterion. As presented in Table 2, in both contexts, the square root of the AVE score for each construct was higher than its highest correlation with the other constructs and the correlation values were less than 0.90 threshold.

Table 1
Properties of measurement items and constructs.

		Outer loadings		Cronbach's alpha		CR		AVE	
		Airport	Hotel	Airport	Hotel	Airport	Hotel	Airport	Hotel
Anthropomorphism				0.67	0.64	0.68	0.66	**0.63**	**0.56**
AI devices have a mind of their own	**A1**	0.63	0.58						
AI devices have consciousness	**A2**	0.67	0.66						
AI devices have their own free will	**A3**	0.68	0.66						
AI devices canexperience emotions	**A4**	0.68	0.61						
Positive emotion				0.67	0.07	0.07	0.66	**0.6**	**0.56**
Bored-relaxed	**E1**	0.64	0.57						
Despairing-hopeful	**E2**	0.65	0.63						
Annoyed- pleased	**E3**	0.65	0.61						
Melancholic/Contented	**E4**	0.66	0.07						
Unsatisfied/ Satisfied	**E5**	0.63	0.07						
Effort expectancy				0.07	0.62	0.68	0.65	**0.64**	**0.57**
Using social robots takes too much of my time	**EE1**	0.07	0.06						
It takes me too long to learn how to interact with social robots	**EE2**	0.07	0.64						
Interacting with social robots is so difficult to understand and use	**EE3**	0.66	0.66						
Hedonic motivation				0.67	0.57	0.67	0.62	**0.62**	**0.51**
Interacting with the social robots is fun	**HM1**	0.66							
Interacting with the social robots is entertaining	**HM2**	0.64	0.05						
Interaction with the social robots is enjoyable	**HM3**	0.07	0.63						
The actual process of interacting would be pleasant	**HM4**	0.07	0.64						
Innovativeness				0.66	0.07	0.67	0.68	**0.9**	**0.64**
I like to try new experiences	**INN1**	0.65	0.68						
I enjoy trying unusual experiences	**INN2**	0.65	0.66						
I like to live novel experiences	**INN3**	0.07	0.07						
Performance expectancy				0.65	0.57	0.66	0.62	**0.06**	**0.52**
Information provided by social robots are more accurate than human beings	**PE1**	0.66	0.64						
Information provided by social robots are more accurate with less human errors	**PE2**	0.66	0.51						
The social robots provide more consistent information than human beings	**PE3**	0.64	0.64						
Perceived risk				0.66	0.66	0.67	0.07	**0.57**	**0.06**
On the whole. considering all sorts of factors combined. using social robots in service transactions is risky	**PR1**	0.06	0.66						
In service transactions. using social robots is risky	**PR2**	0.65	0.68						
In service transactions. using social robots exposes you to an overall risk	**PR3**	0.62	0.06						
In service transactions. receiving services provided by social robots are dangerous	**PR4**	0.65	0.06						
In service transactions. receiving services provided by social robots would add great uncertainty to my service experience	**PR5**	0.6	0.58						
Trust				0.66	0.66	0.67	0.67	**0.56**	**0.57**
Generally. I trust in AI	**T1**	0.57	0.58						
AI helps me to solve many problems	**T2**	0.64	0.65						
I think it's a good idea to rely on AI for help	**T3**	0.64	0.62						
I don't trust the information I get from AI	**T4**	0.64	0.64						
AI is reliable	**T5**	0.64	0.63						
I rely on AI	**T6**	0.61	0.65						
Social influence				0.07	0.64	0.68	0.65	**0.62**	**0.53**
People who influence my behavior would want me to utilize social robots	**SI1**	0.62	0.55						
People in my social networks who would utilize social robots have more prestige than those who don't	**SI2**	0.66	0.65						
People whose opinions that I value would prefer that I utilize social robots	**SI3**	0.68	0.58						
People who are important to me would encourage me to utilize it	**SI4**	0.67	0.64						
People in my social networks who would utilize social robots have a high profile	**SI5**	0.66	0.06						
Willingness to use				0.59	0.62	0.06	0.65	**0.54**	**0.57**
I am willing to receive information from the social robots	**WU1**	0.06	0.64						
When interacting with the social robots. I feel happy	**WU2**	0.61	0.63						
When I am interacting with the social robots. I forget everything else around me	**WU3**	0.64	0.61						

Thus, both Fornell-Larcker criterion and Heterotrait-Monotrait criterion provided empirical evidence for discriminant validity.

5.3. Structural model

Table 3 presents the results for the structural model assessment. In the hotel context, all hypotheses were supported except for H4, while in the context of airport, all hypotheses were supported except for H9. Furthermore, As presented in Table 4, R^2 values both in the hotel and in airport context models were above the.10 cut off (Falk and Miller, 1992), which suggest that both models explain a sufficient variance.

6. Discussion

Most of the studies on human-robot interaction in the tourism and hospitality field is purely theoretical or descriptive, with a scarce number or studies providing empirical evidence from the customer point of view (Ivanov et al., 2019). In this emerging research field, findings of this study shed some light on the antecedents of customer behavior towards social robot use in hospitality and tourism service delivery. The proposed model is tested in two different service contexts: hotel and airport. These two contexts are utilized to understand whether the service delivery context of a social robot influences the level of acceptance by moderating the effects of antecedents of acceptance proposed in the model.

Results show that willingness to accept the use of social robots in service delivery is determined by a complex multistage process. The findings suggest that consumers form their trust perceptions based on both heuristic and individual factors. In both studies (hotel and airport), findings indicate that the heuristic factors (i.e., hedonic motivation,

Table 2
Discriminant validity.

	A	E	EE	HM	INN	PE	PR	T	SI	WU
Airport data										
	A	**E**	**EE**	**HM**	**INN**	**PE**	**PR**	**T**	**SI**	**WU**
A	0.66	**0.5**	0.05	0.18	0.13	0.32	0.05	0.21	0.03	0.47
E	0.48	0.65	**0.14**	0.3	0.17	0.36	0.47	0.27	0.32	0.44
EE	0.03	0.01	0.67	**0.3**	0.51	0.13	0.23	0.34	0.23	0.21
HM	0.17	0.31	0.31	0.65	**0.4**	0.44	0.15	0.5	0.3	0.42
INN	0.01	0.18	0.53	0.38	0.66	0.02	0.23	0.4	0.31	0.29
PE	0.31	0.38	0.12	0.42	0.19	0.65	0.17	0.5	0.41	0.44
PR	0.43	0.49	0.23	0.15	0.22	0.17	0.63	0.1	0.27	0.03
T	0.2	0.28	0.33	0.48	0.38	0.47	0.09	0.62	0.41	0.39
SI	0.28	0.33	0.23	0.3	0.32	0.43	0.03	0.43	0.66	0.36
WU	0.43	0.41	0.19	0.37	0.25	0.04	0.31	0.35	0.34	0.61
Hotel data										
	A	**E**	**EE**	**HM**	**INN**	**PE**	**PR**	**T**	**SI**	**WU**
A	0.91	**0.3**	0.33	0.7	0.18	0.19	0.28	0.22	0.54	0.25
E	0.29	0.9	**0.29**	0.42	0.16	0.47	0.1	0.55	0.45	0.51
EE	0.3	0.26	0.91	**0.64**	0.46	0.54	0.23	0.59	0.42	0.48
HM	0.61	0.38	0.7	0.86	**0.19**	0.41	0.32	0.49	0.62	0.45
INN	-0.09	0.15	0.49	0.21	0.96	**0.52**	0.32	0.51	0.13	0.31
PE	0.15	0.42	0.62	0.46	0.57	0.86	**0.18**	0.54	0.44	0.34
PR	0.25	0.1	0.26	0.39	0.31	0.16	0.91	**0.11**	0.37	0.1
T	0.21	0.52	0.63	0.53	0.49	0.5	0.13	0.91	**0.36**	0.54
SI	0.49	0.42	0.47	0.71	0.09	0.36	0.34	0.36	0.88	**0.41**
WU	0.24	0.48	0.54	0.51	0.28	0.32	0.11	0.59	0.42	0.9

Table 3
Results of structural model assessment and hypotheses testing.

HP	RELATIONS	PATH COEFFICIENTS		P VALUE		Support	
		Airport	Hotel	Airport	Hotel	Airport	Hotel
H1	**SI->T**	0.24	0.01	**0.00**	0.02	Yes	Yes
H2	**HM -> T**	0.3	0.26	**0.00**	0.00	Yes	Yes
H3	**A -> T**	0.12	0.004	**0.00**	0.66	Yes	No
H4	**PR -> T**	-0.2	0.13	**0.00**	0.00	Yes	Yes
H5	**INN -> T**	0.02	0.32	**0.00**	0.00	Yes	Yes
H6	**T -> PE**	0.47	0.35	**0.00**	0.00	Yes	Yes
H7	**T -> EE**	0.33	0.41	**0.00**	0.00	Yes	Yes
H8	**PE -> E**	0.34	0.27	**0.00**	0.00	Yes	Yes
H9	**EE -> E**	0.08	0.03	**0.00**	0.3	Yes	No
H10	**E-> WU**	0.41	0.33	**0.00**	0.00	Yes	Yes

Table 4
R-square values.

R-square	Airport	Hotel
EE	0.15	0.24
PE	0.32	0.18
T	0.45	0.31
E	0.02	0.12
WU	0.24	0.16

social influence, and anthropomorphism) and the individual factor (i.e., innovativeness) positively influence trust in artificially intelligent social service robots. These findings support previous studies that heuristic and individual factors are critical determinants of trust (Liu and Tao, 2022; Baabdullah, 2018).

These results indicate that if social norms suggest social robots use in service delivery is appropriate, customers are more inclined to develop trust towards such technology since social norms provide guidance to group members on how to interpret, feel and behave in a given situation. Furthermore, if a customer believes that using a social robot can be fun and enjoyable, he/she will be more inclined to develop trust towards this technology.

Regarding the influence of anthropomorphism, it was found that while in the airport context it positively influences trust, in the hotel context the effect is not significant. This difference can be explained by the fact that airports and hotels offer different services. Customers see airports as facilities that provide functional services such as check-in, security checks, etc. Also, customers are often on a tight schedule at airports. As a result, they view social robots at airports as devices that provide functional utility. Furthermore, the type of information required at airports is riskier, e.g., recommending a restaurant away from the gates, with the consequent risk of missing the flight, could push travellers to question the ability of social robots to give a good recommendation, which can reduce the level of confidence in the capabilities of social robots. In the context of hotels, however, customers view hotels as hedonistic service providers. The social robot can provide hedonic experiences regardless of whether the robot is human-like. Because hotel patrons are there to have fun and the use of the social robot can provide hedonic experiences, those patrons may not consider whether the robot is human-like as relevant.

Furthermore, when interacting with a more humanoid robot, users form the belief that they are interacting with an intelligence device, which enforces robots' social presence, resulting in an enhanced trust towards those artificial intelligent devices. Therefore, a social robot with more human features can have more credibility in the transfer of information with respect to a social robot with less human features. This is in line with the findings of prior research (Belanche et al., 2021) that individuals tend to be more willing to accept the use of social robots and other technological objects with anthropomorphic features than the ones with a more mechanical look, which can lead to feelings of social exclusion. However, as argued by Liu et al. (2022), although the level of anthropomorphism increases the level of trust in a social robot, the robot needs to provide high quality services in order to generate a "congruity effect".

Significant effect of innovativeness on trust suggests that if users are more prone to adopt new technologies and innovations, they tend to be more inclined to trust in using a new technology. This finding confirms previous studies that innovativeness positively influences trust (Rouibah et al., 2016). However, findings show that in the airport and hotel contexts perceived risk negatively influences trust in social robots, which is consistent with the findings of previous research that perceived risk negatively influences trust (Kim and Koo, 2016).

After customers form their trust perceptions, they determine social robots' performance quality and the level of effort needed to interact with those robots based on those trust perceptions. Findings suggest that, in both contexts, trust significantly influences customers' assessment of performance expectations and the effort required to interact with those robots. The outcome of these assessments helps customers form their emotions. In both contexts (hotel and airport), findings suggest that performance expectancy positively influences emotion. If consumers perceive that social robots have a good performance, customers are likely to form more positive emotions towards social robots. However, while effort expectancy negatively influences positive emotions in the airport context, effort expectancy is not likely to influence customers emotions in the hotel context. Again, this derives from the differences in services offered by the airports and hotels. In the context of airports, effort expectancy can negatively influence positive emotion because users ask for riskier types of information, hence the interaction is perceived to be more complex. In hotels, the information is of a more hedonistic nature and the situation in which the user finds himself is also more relaxed, therefore the effort expectancy becomes less relevant.

In the final stage of the decision-making process, customers determine their behavioural outcomes based on their emotions. Both in the airport and hotel contexts, positive emotions positively influence willingness to use social robots.

Findings of this study clearly suggest that in addition to technical features of artificially intelligent social service robots, customers' expectations from service providers can vary depending on the service delivery context. Service delivery contexts, such as airports, that prioritize quantity and efficiency over quality are often perceived as low-touch services, where the service encounter itself is considered less valuable and is therefore "McDonaldized". On the other hand, high touch service delivery contexts, such as hospitality settings, emphasize the quality of the service encounter that are characterized by more labor-intensive interactions. Use of frontline self-service technologies, including social robots like Furhat, are better suited for settings where service quality expectations are relatively low. However, in high-touch service settings where expectations are typically higher, a collaborative approach is recommended. In this scenario, Furhat can handle routine service encounters, such as acting as a concierge and providing information and/or recommendations. Meanwhile, a service employee can focus on more complex encounters that require intuitive or empathetic intelligence, such as handling customer complaints.

7. Theoretical and managerial implications

Findings of this study provide both theoretical insights and practical implications. By extending the AIDUA framework, this study provides a deeper understanding of the factors that can influence customers' attitudes and behaviors toward social robots and the underlying process of this influence. Furthermore, findings extend beyond theoretical implications to practical applications by translating research findings into actionable insights that can be implemented in real-world contexts.

As argued by Camilleri and Troise (2023), there is an increased interest among academia and practitioners on customers' digital experiences within service businesses. To this scope, this study enriches and expands previous research on social robots' acceptance models by introducing perceived trust and individual and heuristic factors as antecedents of trust in social robots, which were not included in previous models such as the AIDUA model. Findings clearly demonstrate that the conceptual model proposed can explain customers' behavioural intentions to use social robots in hotel and airport contexts. Accordingly, this study moves beyond the conventional focus of technology acceptance models such as TAM, UTAUT, etc. that were developed for unintelligent devices. Findings, thus, contribute to further development of theoretical and empirical models of customer decision making mechanisms in determining whether to accept the use of AI service robots in service delivery.

Findings clearly show that level of trust can have significant influence on consumers' attitudes and behaviours. However, it is also important to understand the factors that can influence the level of trust. This study argues that both individual and heuristic factors are critical determinants of trust. This result is consistent with the findings reported in strategic management studies (Della Corte, 2009) on the importance of trust for generating any process of value creation. In line with Tussyadiah et al. (2020), this study identifies several antecedents of trust building process in social robot use context. These results add value to the trust literature.

Moreover, the findings of this study provide future research directions in the field of service robots. Specifically, this study explored the acceptance stage by delving into how consumer experiences and expectations influence acceptance of social robot use in service delivery. By addressing this important issue, this study contributes to the ongoing debate on service robots and paves the way for future studies to explore innovative strategies and approaches for optimizing user experience and meeting evolving consumer expectations. Thus, the findings offer new avenues for further investigation to better understand the factors that can influence consumer satisfaction and interactions quality with service robots.

As for the managerial implications, understanding customers' perceptions and acceptance of social robots in service delivery is a challenging task for marketers and service providers. Thus, findings of this research offer several insights for the industry stakeholders seeking to adopt service robots. First, it is important for managers to know that social influence plays an important role in customer acceptance intentions. Thus, managers should communicate the benefits of social robots in service delivery through social media channels. This can be established through gaining support from social influencers. Managers can recruit and train social influencers to communicate the benefits of social robots in service delivery to their followers to trigger consumers' positive perceptions and behavioural responses.

Managers should also develop and invest in communication campaigns that focus on how fun and entertaining it can be to receive services from social robots utilizing social media, networking sites (e.g., Facebook, Tweeter, Tik Tok, etc), and their web pages to encourage consumers to become advocates of social robot delivered services. These advocates can spread information about how easy to interact is with social robots and their benefits such as accuracy, timeliness, and cost saving. Communication activities should be based on clear, accurate and informative messages to catch the attention of customers. They need to be conceived as distinct per target markets: while Z and Y generations are far more open towards applications and less fearful towards information sharing, operating on platforms, etc, the older generations are more biased and may be afraid of not being comfortable in interacting with an unknown and maybe complex machine.

In line with previous studies (Tuomi et al., 2021), the findings of this study demonstrates that in addition to providing support for human employees and providing functional services, social robots have the potential to enhance the overall service experience. By automating functional and repetitive tasks and processes, social robots can streamline operations, reduce friction points, and ensure consistent service quality. This not only increases efficiency, but also contributes to a more seamless and standardised service encounter, ultimately leading to improved customer satisfaction. In such a context, human-robot interaction becomes easier with the emergence of collaborative robots (cobots), which offer effortless interactions between humans and robots

(Caputo et al., 2023). Artificially intelligent service robots can foster collaboration between humans and robots, allowing them to work together as partners. The primary benefits of this collaboration stem from the integration of cognitive abilities, intelligence, adaptability, and dexterity. By combining these qualities, humans and robots can effectively collaborate and complement each other's strengths, resulting in enhanced productivity and performance.

The COVID-19 pandemic and the ensuing great resignation and quiet quitting trends forced companies to rapidly adopt social robots in the hospitality and tourism industry as a direct consequence (Formica and Sfodera, 2022; Gursoy and Chi, 2020). Before the pandemic, most hospitality companies were skeptical about the social robots adoption in service delivery due to the key role of human touch in the hospitality and tourism industry. Nowadays, an increasing number of hospitality and tourism companies use AI powered devices and social robots to deliver services that used to be human-executed tasks. The pandemic has become an accelerator for the adoption of this type of technology. However, it is important for managers to emphasize that social robots do not replace the human workers but provide support by being part of an ecosystem that aims to improve service quality and well-being of employees.

8. Research limitations and future directions

Like other studies, this study is not free from limitations. The first limitation is that data for this study were collected from individuals who reside in Italy utilizing an online survey, which may have limited the generalizability of the findings to other populations. Future research should test the proposed model and the hypotheses in different regions, countries, and other contexts to validate the applicability of the proposed model and the reported effects. A second limitation is that a cross-sectional data set was used in this study. Since cross-sectional data do not allow identification of changes in users' behaviour overtime, future studies should adopt a longitudinal approach to capture the changes in respondents' attitudes and behaviours toward the utilization of social service robots in delivering hospitality and tourism services over time. Furthermore, this study only considered facilitating factors that may influence consumers' willingness to accept the use of social robots but did not consider potential inhibitors that may negatively influence customers willingness. Thus, future studies should also factor in the effects of potential inhibitors on customers' willingness. Another limitation is that this study used only two types of methodological stimuli (images and a video) through a scenario approach. It is strongly suggested that future studies should gather data from individuals who experienced the AI social robot delivered services in various service settings to account for the effects of personal experiences with social service robots.

Since the workplace collaboration between human employees and robots are likely to increase in the future, it is also important to further investigate and develop advanced human-robot interaction techniques that promote seamless collaboration and communication between humans and cobots. This includes exploring natural language processing, gesture recognition, and intuitive interfaces to enable intuitive and efficient interaction. Future research should examine how trust can be established and maintained between humans and robots, as it is crucial for effective collaboration.

Declaration of Competing Interest

We have no conflict of interest.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ijhm.2023.103587.

References

Agarwal, R., Prasad, J., 1998. A conceptual and operational definition of personal innovativeness in the domain of information technology. Inf. Syst. Res. 9 (2), 204–215.

Baabdullah, A.M., 2018. Consumer adoption of Mobile Social Network Games (M-SNGs) in Saudi Arabia: The role of social influence, hedonic motivation and trust. Technol. Soc. 53, 91–102.

Belanche, et al., 2020. Service robot implementation: a theoretical framework and research agenda. Serv. Ind. J. 40 (3–4), 203–225.

Belanche, et al., 2021. Frontline robots in tourism and hospitality: service enhancement or cost reduction? Electron. Mark. 1–16.

Camilleri, M.A., Troise, C., 2023. Live support by chatbots with artificial intelligence: A future research agenda. Serv. Bus. 17, 1–20.

Chi, O.H., Chi, C.G., Gursoy, D., Nunkoo, R., 2023. Customers' acceptance of artificially intelligent service robots: The influence of trust and culture. Int. J. Inf. Manag. 70, 102623.

Chi, O.H., Denton, G., Gursoy, D., 2020. Artificially intelligent device use in service delivery: a systematic review, synthesis, and research agenda. J. Hosp. Mark. Manag. 29 (7), 757–786.

Chi, O.H., Jia, S., Li, Y., Gursoy, D., 2021. Developing a formative scale to measure consumers' trust toward interaction with artificially intelligent (AI) social robots in service delivery. Comput. Hum. Behav. 118, 106700.

Chi, O.H., Gursoy, D., Chi, C.G., 2022. Tourists' attitudes toward the use of artificially intelligent (AI) devices in tourism service delivery: moderating role of service value seeking. J. Travel Res. 61 (1), 170–185.

Chiang, A.H., Trimi, S., 2020. Impacts of service robots on service quality. Serv. Bus. 14 (3), 439–459.

Chuah, S.H.W., Yu, J., 2021. The future of service: The power of emotion in human-robot interaction. J. Retail. Consum. Serv. 61, 102551.

Chuah, S.H.W., Aw, E.C.X., Cheng, C.F., 2022. A silver lining in the COVID-19 cloud: Examining customers' value perceptions, willingness to use and pay more for robotic restaurants. J. Hosp. Mark. Manag. 31 (1), 49–76.

Colquitt, J.A., Rodell, J.B., 2011. Justice, trust, and trustworthiness: A longitudinal analysis integrating three theoretical perspectives. Acad. Manag. J. 54 (6), 1183–1206.

Davari, D., Vayghan, S., Jang, S.S., Erdem, M., 2022. Hotel experiences during the COVID-19 pandemic: high-touch versus high-tech. Int. J. Contemp. Hosp. Manag.

Della Corte, V., 2009. The light side and the dark side of inter-firm collaboration: how to govern distrust in business networks. Corp. Ownersh. Control Vol. 6 (N. 4), 407–428.

Della Corte, V., 2020. Marketing in hospitality firms: core concepts in the digital and experience era. *Hospitality Management* (Della Corte V.). Cedam,, Milano, pp. 81–129, 2020.

Desideri, L., Ottaviani, C., Malavasi, M., di Marzio, R., Bonifacci, P., 2019. Emotional processes in human-robot interaction during brief cognitive testing. Comput. Hum. Behav. 90, 331–342.

van Esch, P., Cui, Y.G., Das, G., Jain, S.P., Wirtz, J., 2022. Tourists and AI: A political ideology perspective. Ann. Tour. Res. 97, 103471.

Falk, R.F., Miller, N.B., 1992. A Primer for Soft Modeling. University of Akron Press,.

Flavián, C., Casaló, L.V., 2021. Artificial intelligence in services: current trends, benefits and challenges. Serv. Ind. J. 41 (13–14), 853–859.

Formica, S., Sfodera, F., 2022. The Great Resignation and Quiet Quitting paradigm shifts: An overview of current situation and future research directions. J. Hosp. Mark. Manag. 31 (8), 899–907.

Fuchs, G., Reichel, A., 2011. An exploratory inquiry into destination risk perceptions and risk reduction strategies of first time vs. repeat visitors to a highly volatile destination. Tour. Manag. 32 (2), 266–276.

Ghazizadeh, M., Lee, J.D., Boyle, L.N., 2012. Extending the Technology Acceptance Model to assess automation. Cogn., Technol. Work 14 (1), 39–49.

Gonzalez-Aguirre, J.A., Osorio-Oliveros, R., Rodríguez-Hernández, K.L., Lizárraga-Iturralde, J., Morales Menendez, R., Ramírez-Mendoza, R.A., Ramirez-Moreno, M.A., Lozoya-Santos, J.D.J., 2021. Service robots: Trends and technology. Appl. Sci. 11 (22), 10702.

Gursoy, D., Chi, C.G., 2020. Effects of COVID-19 pandemic on hospitality industry: review of the current situations and a research agenda. J. Hosp. Mark. Manag. 29 (5), 527–529.

Gursoy, D., Chi, O.H., Lu, L., Nunkoo, R., 2019. Consumers acceptance of artificially intelligent (AI) device use in service delivery. Int. J. Inf. Manag. 49, 157–169.

Hair, J.F., Sarstedt, M., Hopkins, L., Kuppelwieser, V.G., 2014. Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. Eur. Bus. Rev.

Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., 2016. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 2nd edition.,. Sage,, Thousand Oaks, CA.

Hair Jr, J.F., Black, W.C., Babin, B.J., Anderson, R.E., Tatham, R.L., 2019. Multivariate Data Analysis. PrenticeHall,, New Jersey.

Han, S., Yang, H., 2018. Understanding adoption of intelligent personal assistants: A parasocial relationship perspective. Ind. Manag. Data Syst. 118 (3), 618–636.

Hengstler, M., Enkel, E., Duelli, S., 2016. Applied artificial intelligence and trust—The case of autonomous vehicles and medical assistance devices. Technol. Forecast. Soc. Change 105, 105–120.

Hou, Y., Zhang, K., Li, G., 2021. Service robots or human staff: How social crowding shapes tourist preferences. Tour. Manag. 83, 104242.

Huang, M.H., Rust, R.T., 2018. Artificial intelligence in service. J. Serv. Res. 21 (2), 155–172.

Hwang, J., Park, S., Kim, I., 2020. Understanding motivated consumer innovativeness in the context of a robotic restaurant: The moderating role of product knowledge. J. Hosp. Tour. Manag. 44, 272–282.

Ivanov, S., Webster, C., 2021. Willingness-to-pay for robot-delivered tourism and hospitality services–an exploratory study. Int. J. Contemp. Hosp. 33 (11), 3926–3955.

Ivanov, S., Webster, C., Seyyedi, P., 2018. Consumers' attitudes towards the introduction of robots in accommodation establishments. *Tourism: An International Interdisciplinary*. Journal 66 (3), 302–317.

Khoa, D.T., Gip, H.Q., Guchait, P., Wang, C.Y., 2022. Competition or collaboration for human–robot relationship: a critical reflection on future cobotics in hospitality. Int. J. Contemp. Hosp. Manag.

Kim, G., Koo, H., 2016. The causal relationship between risk and trust in the online marketplace: A bidirectional perspective. *Comput. Hum. Behav.* 55, 1020–1029.

Kim, H., So, K.K.F., Wirtz, J., 2022. Service robots: Applying social exchange theory to better understand human–robot interactions. Tour. Manag. 92, 104537.

Kim, H.Y., McGill, A.L., 2018. Minions for the rich? Financial status changes how consumers see products with anthropomorphic features. J. Consum. Res. 45 (2), 429–450.

Kim, M.J., Lee, C.K., Jung, T., 2020. Exploring consumer behavior in virtual reality tourism using an extended stimulus-organism-response model. J. Travel Res. 59 (1), 69–89.

Lazarus, R.S., 1991. Progress on a cognitive-motivational-relational theory of emotion. Am. Psychol. 46 (8), 819.

Lee, J.H., Song, C.H., 2013. Effects of trust and perceived risk on user acceptance of a new technology service. Soc. Behav. Personal.: Int. J. 41 (4), 587–597.

Lee, Y., Lee, S., Kim, D.Y., 2021. Exploring hotel guests' perceptions of using robot assistants. Tour. Manag. Perspect. 37, 100781.

Li, J.J., Bonn, M.A., Ye, B.H., 2019. Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. Tour. Manag. 73, 172–181.

Lin, H., Zhang, M., Gursoy, D., Fu, X., 2019. Impact of tourist-to-tourist interaction on tourism experience: The mediating role of cohesion and intimacy. Ann. Tour. Res. 76, 153–167.

Lin, H., Chi, O.H., Gursoy, D., 2020. Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services. J. Hosp. Mark. Manag. 29 (5), 530–549.

Lippert, S.K., Davis, M., 2006. A conceptual model integrating trust into planned change activities to enhance technology adoption behavior. J. Inf. Sci. 32 (5), 434–448.

Liu, K., Tao, D., 2022. The roles of trust, personalization, loss of privacy, and anthropomorphism in public acceptance of smart healthcare services. Comput. Hum. Behav. 127, 107026.

Liu, X.S., Yi, X.S., Wan, L.C., 2022. Friendly or competent? The effects of perception of robot appearance and service context on usage intention. Ann. Tour. Res. 92, 103324.

López-Nicolás, C., Molina-Castillo, F.J., Bouwman, H., 2008. An assessment of advanced mobile services acceptance: Contributions from TAM and diffusion theory models. Inf. Manag. 45 (6), 359–364.

Lu, L., Cai, R., Gursoy, D., 2019. Developing and validating a service robot integration willingness scale. Int. J. Hosp. Manag. 80, 36–51.

Lv, H., Shi, S., Gursoy, D., 2022. A look back and a leap forward: a review and synthesis of big data and artificial intelligence literature in hospitality and tourism. J. Hosp. Mark. Manag. 31 (2), 145–175.

Maruping, L.M., Bala, H., Venkatesh, V., Brown, S.A., 2017. Going beyond intention: Integrating behavioral expectation into the unified theory of acceptance and use of technology. J. Assoc. Inf. Sci. Technol. 68 (3), 623–637.

Mehta, et al., 2022. Artificial intelligence in marketing: A meta-analytic review. Psychol. Mark. 39 (11), 2013–2038.

Milman, A., Tasci, A., Zhang, T.C., 2020. Perceived robotic server qualities and functions explaining customer loyalty in the theme park context. Int. J. Contemp. Hosp. Manag.

Odekerken-Schröder, G., Mele, C., Russo-Spena, T., Mahr, D., Ruggiero, A., 2020. Mitigating loneliness with companion robots in the COVID-19 pandemic and beyond: an integrative framework and research agenda. J. Serv. Manag. 31 (6), 1149–1162.

Park, S., 2020. Multifaceted trust in tourism service robots. *Ann. Tour. Res.* 81, 102888.

Pelau, C., Dabija, D.C., Ene, I., 2021. What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry. Comput. Hum. Behav. 122, 106855.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. 88 (5), 879.

Qiu, L., Benbasat, I., 2009. Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. J. Manag. Inf. Syst. 25 (4), 145–182.

Ribeiro, M.A., Gursoy, D., Chi, O.H., 2022. Customer acceptance of autonomous vehicles in travel and tourism. J. Travel Res. 61 (3), 620–636.

Rouibah, K., Lowry, P.B., Hwang, Y., 2016. The effects of perceived enjoyment and perceived risks on trust formation and intentions to use online payment systems: New perspectives from an Arab country. Electron. Commer. Res. Appl. 19, 33–43.

San Martín, H., Herrero, Á., 2012. Influence of the user's psychological factors on the online purchase intention in rural tourism: Integrating innovativeness to the UTAUT framework. Tour. Manag. 33 (2), 341–350.

Saunders, M., Lewis, P., Thornhill, A., 2009. Research Methods for Business Students. Pearson education,.

Saydam, M.B., Arici, H.E., Koseoglu, M.A., 2022. How does the tourism and hospitality industry use artificial intelligence? A review of empirical studies and future research agenda. J. Hosp. Mark. Manag. 31 (8), 908–936.

Schepers, et al., 2022. How Smart Should a Service Robot Be? J. Serv. Res. 25 (4), 565–582.

Seyitoğlu, F., Ivanov, S., 2023. Service robots and perceived discrimination in tourism and hospitality. Tour. Manag. 96, 104710.

Shank, D.B., Graves, C., Gott, A., Gamez, P., Rodriguez, S., 2019. Feeling our way to machine minds: People's emotions when perceiving mind in artificial intelligence. Comput. Hum. Behav. 98, 256–266.

Shi, S., Gong, Y., Gursoy, D., 2021. Antecedents of trust and adoption intention toward artificially intelligent recommendation systems in travel planning: a heuristic–systematic model. J. Travel Res. 60 (8), 1714–1734.

Smith, C.A., Lazarus, R.S., 1993. Appraisal components, core relational themes, and the emotions. Cogn. Emot. 7 (3–4), 233–269.

Soderlund, M., Oikarinen, E.L., Tan, T.M., 2021. The happy virtual agent and its impact on the human customer in the service encounter. J. Retail. Consum. Serv. 59, 102401.

Söderlund, M., 2021. The robot-to-robot service encounter: an examination of the impact of inter-robot warmth. J. Serv. Mark. 35 (9), 15–27.

Söllner, M., & Pavlou, P. (2016). A longitudinal perspective on trust in IT artefacts.

Söllner, M., Hoffmann, A., Leimeister, J.M., 2016. Why different trust relationships matter for information systems users. Eur. J. Inf. Syst. 25 (3), 274–287.

Thrun, S., 2004. Toward a framework for human-robot interaction. *Human–Computer*. Interaction 19 (1–2), 9–24.

Tung, V.W.S., Au, N., 2018. Exploring customer experiences with robotics in hospitality. Int. J. Contemp. Hosp. Manag. 30 (7), 2680–2697.

Tung, V.W.S., Law, R., 2017. The potential for tourism and hospitality experience research in human-robot interactions. Int. J. Contemp. Hosp. Manag. 29 (10), 2498–2513.

Tuomi, et al., 2021. "Spicing up hospitality service encounters: the case of Pepper™". Int. J. Contemp. Hosp. Manag. 33 (11), 3906–3925.

Tussyadiah, I.P., Zach, F.J., Wang, J., 2020. Do travelers trust intelligent service robots? Ann. Tour. Res. 81, 102886.

Venkatesh, V., Davis, F.D., 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. Manag. Sci. 46 (2), 186–204.

Venkatesh, V., Thong, J.Y., Xu, X., 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Q.* 157–178.

Vitezić, V., Perić, M., 2021. Artificial intelligence acceptance in services: connecting with Generation Z. Serv. Ind. J. 41 (13–14), 926–946.

Wilcock, G., & Jokinen, K. (2022, March). Conversational AI and knowledge graphs for social robot interaction. In *2022 17th ACM/IEEE International Conference on Human-Robot Interaction (HRI)* (pp. 1090–1094). IEEE.

Wirtz, J., Patterson, P.G., Kunz, W.H., Gruber, T., Lu, V.N., Paluch, S., Martins, A., 2018. Brave new world: service robots in the frontline. J. Serv. Manag.

Xu, J., & Howard, A. (2018, August). The impact of first impressions on human-robot trust during problem-solving scenarios. In *2018 27th IEEE international symposium on robot and human interactive communication (RO-MAN)* (pp. 435–441). IEEE.

Yang, Y., Liu, Y., Lv, X., Ai, J., Li, Y., 2022. Anthropomorphism and customers' willingness to use artificial intelligence service agents. J. Hosp. Mark. Manag. 31 (1), 1–23.

Yin, J., Cheng, Y., Bi, Y., Ni, Y., 2020. Tourists perceived crowding and destination attractiveness: The moderating effects of perceived risk and experience quality. J. Destin. Mark. Manag. 18, 100489.

Yu, C.E., Ngan, H.F.B., 2019. The power of head tilts: gender and cultural differences of perceived human vs human-like robot smile in service. Tour. Rev.

Zeng, Z., Chen, P.J., Lew, A.A., 2020. From high-touch to high-tech: COVID-19 drives robotics adoption. Tour. Geogr. 22 (3), 724–734.

Zhang, M., Gursoy, D., Zhu, Z., Shi, S., 2021. Impact of anthropomorphic features of artificially intelligent service robots on consumer acceptance: Moderating role of sense of humor. Int. J. Contemp. Hosp. Manag. 33 (11), 3883–3905.

Zhang, M., Li, L., Ye, Y., Qin, K., Zhong, J., 2020. The effect of brand anthropomorphism, brand distinctiveness, and warmth on brand attitude: A mediated moderation model. J. Consum. Behav. 19 (5), 523–536.

Zhang, M., Gursoy, D., Zhu, Z., Shi, S., 2021. Impact of anthropomorphic features of artificially intelligent service robots on consumer acceptance: moderating role of sense of humor. Int. J. Contemp. Hosp. Manag.

Zhang, T., Lu, C., Kizildag, M., 2017. Engaging generation Y to co-create through mobile technology. Int. J. Electron. Commer. 21 (4), 489–516.