1-1-2023

Consumer intention to use service robots: A cognitive–affective–conative framework

Dan Huang

Qiurong Chen

Songshan (Sam) Huang
Edith Cowan University

Xinyi Liu

10.1108/IJCHM-12-2022-1528
This is an Authors Accepted Manuscript version of an article published by Emerald in *International Journal of Contemporary Hospitality Management*. The published version is available at: https://doi.org/10.1108/IJCHM-12-2022-1528
Huang, D., Chen, Q., Huang, S., Liu, X. (2023). Consumer intention to use service robots: a cognitive–affective–conative framework. International Journal of Contemporary Hospitality Management. Advance online publication. https://doi.org/10.1108/IJCHM-12-2022-1528

Consumer intention to use service robots: a cognitive-affective-conative framework

Abstract

Purpose – Drawing on the cognitive-affective-conative framework, this study aims to develop a model of service robot acceptance in the hospitality sector by incorporating both cognitive evaluations and affective responses.

Design/methodology/approach – A mixed-method approach combining qualitative and quantitative methods was employed to develop measurement and test research hypotheses.

Findings – The results show that five cognitive evaluations (i.e., cuteness, coolness, courtesy, utility, and autonomy) significantly influence consumers' positive affect, leading to customer acceptance intention. Four cognitive evaluations (cuteness, interactivity, courtesy, and utility) significantly influence consumers' negative affect, which in turn positively affects consumer acceptance intention.

Practical implications – This study provides significant implications for the design and implementation of service robots in the hospitality and tourism sector.

Originality/value – Different from traditional technology acceptance models, this study proposed a model based on the hierarchical relationships of cognition, affect, and conation to enhance knowledge about human-robot interactions.

Keywords Service robots, Consumer intention, Cognitive evaluations, Affective responses, Technology acceptance, Cognitive-affective-conative framework

Paper type Research paper

1. Introduction

Service robots are being increasingly applied across various industries (e.g., hospitality, healthcare, and aged care), owing to advancements in automation, machine learning and artificial intelligence. The global market value of service robotics is estimated to reach USD 41. 49 billion by 2027 (Fortune, 2020). Service robots are favoured for their competitive advantages such as low cost and accuracy (Ivanov *et al*., 2022; Ozdemir *et al*., 2023). The Covid-19 pandemic has further accelerated the adoption of service robots in various service sectors due to the need for social distancing measures (Chi *et al*., 2020). In the hospitality sector specifically, robots have been used to deliver a range of services such as offering reception services in hotels (Fu *et al*., 2022), preparing food and beverage (Guan *et al*., 2022), and delivering various items (Ivanov and Webster, 2021).

The increasing application of service robots has profoundly transformed service practices and created new interaction possibilities (Belanche *et al*., 2020c; Khoa *et al*., 2023). As such, an emerging body of literature has paid attention to consumer responses to service robots (e.g., Belanche *et al*., 2019; Belanche *et al*., 2020b; Byrd *et al*., 2021; Kim *et al*., 2022; Romero and Lado, 2021). Among the burgeoning literature on human-robot interactions, consumer acceptance (i.e., willingness to use or intention to use) is a major topic (Ivanov *et al.*, 2019; Law *et al*., 2022). Understanding consumer acceptance is important as consumers' positive responses (e.g., acceptance and willingness-to-pay) to service robots are a driving force for hospitality companies to invest in such innovation (Belanche *et al*., 2021; Schepers *et al*., 2022), which indirectly brings benefits to robot distributors and manufacturers (Ivanov and Webster, 2021).

Despite advances in research on consumer acceptance of service robots (e.g., Gursoy *et al*., 2019; Lu *et al*., 2019; Wirtz *et al*., 2018), much remains to be explored (Ivanov and Webster, 2019). First, most studies have employed a cognitive perspective (e.g., Shin and Jeong, 2020), leaving a gap in understanding how cognition and emotion jointly shape consumer behavioural intentions. Consumer emotions play an important role in explaining willingness to interact with and accept artificially intelligent services (Blut *et al*., 2021; Flavián and Casaló, 2021; Gursoy *et al*., 2019). Neglecting the impact of cognitive appraisals and emotions could lead to misjudging consumer behaviour in automated service settings (Schepers *et al*., 2022). Second, many studies have relied on hypothetical scenarios, paying less attention to consumer responses after actual usage. Perceptions of service robots during real-world interactions may differ from those observed in laboratory settings. Ivanov and Webster (2021) thus acknowledged that "asking respondents who have actually used robots in a tourism context might have elicited more valid results" (pp. 3942-3943).

This study addresses the research gaps identified above by applying the cognitive-affective-conative framework to examine consumer acceptance of service robots in hospitality. Specifically, it focuses on consumers with actual experience with service robots. This study selected variables based on the relevant findings of Huang *et al*. (2021). The rationale for this is two-fold: first, consumer cognitive evaluations and emotions identified by Huang *et al*. (2021) were grounded in real-world human-robot interactions, which aligns with the focus of this study; second, the variables identified in Huang *et al*. (2021) were based on a robust analysis of a large amount of real-life data, providing a solid foundation for this study.

This study has two research objectives:

1. Develop measurements of consumer cognitive evaluations and affective responses in human-robot interactions.

2. Identify how cognitive evaluations and affective responses shape customer intention to use service robots.

2. Literature review and hypotheses development

2.1 Consumer intention to use service robots

Consumer intention to use service robots is a rapidly growing topic in hospitality research. Based on prior literature (e.g., Gursoy *et al*., 2019), this study defines consumer acceptance of service robots as the behavioural intention to use them. While acceptance can be understood from different actors (Shin, 2022), this study focuses on consumers' acceptance.

Research on consumer intention to use service robots can be classified into two streams. The first stream relies on traditional technology acceptance models, e.g., the technology acceptance model (TAM) (Davis, 1989) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh *et al*, 2003), along with their extensions. These models mainly focus on utilitarian-based concepts and have been applied in various robot service contexts (e.g., Lu *et al*., 2019). Scholars have also integrated the traditional models with other theories and variables. For instance, Boo and Chua (2022) combined TAM with privacy calculus theory, incorporating variables such as hotel guests' personal innovativeness as influential factors of service robot acceptance. Traditional acceptance models, originally designed for non-intelligent technologies, may not fully explain the acceptance of service robots, as robots nowadays possess human-like intelligence and interact with consumers in a manner similar to human frontline employees, distinguishing them from traditional technologies (Chi *et al*., 2020; Gursoy *et al*., 2019; Lu *et al*., 2019).

The limitations of traditional models have thus led to the emergence of the second research stream to develop new theoretical frameworks that can better capture the unique characteristics of these technologies and their impact on consumer acceptance. Scholars have developed models such as the artificially intelligent device use acceptance (AIDUA) model (Gursoy *et al*., 2019) and service robot acceptance model (sRAM) (Wirtz *et al*., 2018), which incorporate intelligent features such as sociability, anthropomorphism, and relational value. Furthermore, alternative theoretical perspectives, such as attribution theory (Belanche *et al*., 2020a), construal level theory (Cai *et al*., 2022), social exchange theory (Kim *et al*., 2022), stereotype content model (Liu *et al*., 2022), and psychological ownership theory (Ruiz-Equihua *et al*., 2022), have been employed to enhance understanding of service robot acceptance.

While progress has been made in understanding customer acceptance of service robots, there are still gaps to address. Previous research has primarily focused on utilitarian and anthropomorphic aspects, lacking diverse perspectives (Fernandes and

Oliveira, 2021). Additionally, the psychological implications of customer interactions with service robots have been overlooked, particularly the impact of emotions on intention and behaviour (Akdim *et al*., 2021; Tuomi *et al*., 2021). Thus, this study aims to employ the cognitive-affective-conative framework to investigate the influence of cognitive evaluations and affective responses on the intention to use service robots.

2.2 Human-robot interactions based on the cognitive-affective-conative framework

The cognitive-affective-conative framework, rooted in the cognitive appraisal theory and cognitive-motivational-relational theory of emotion (Lazarus, 1991; Lazarus and Folkman, 1984), suggests that individuals' cognitive evaluations of events shape their emotional reactions, which subsequently impact their behaviour (Bagozzi, 1992). This framework consists of three stages: appraisal processes, emotional reactions, and coping responses.

Appraisal processes reflect the cognitive component, where individuals evaluate their internal or situational conditions and form their evaluations (Lazarus, 1991). The evaluated object is related to the "outcome" (Bagozzi , 1992). In the literature, cognitive appraisal is usually captured by individuals' perception of the attributes of an object, e.g., perceived performance (Chi *et al*., 2020).

Emotional reactions, referring to subjective feelings evoked by appraising a consumption experience (Mano and Oliver, 1993), represent the affective component in the framework. The variation (e.g., quality and intensity) of the emotional reactions is determined by subjective cognitive appraisals of an event or experience (Lazarus, 1991).

Coping responses refer to the conative component of the framework. Individuals can use avoidance or approach behaviour as a coping strategy (Lazarus, 1991). When an individual experiences an unpleasant event, an *outcome-desire conflict* occurs, leading to negative emotions (Bagozzi, 1992). They may cope with the harmful condition by avoiding the event (Lazarus and Folkman, 1984). An *outcome-desire fulfillment* may arise when an individual experiences a pleasant event, resulting in positive emotions, which then stimulate approach behaviour (Bagozzi, 1992).

The cognitive-affective-conative framework has been applied in hospitality and tourism research. For example, Li *et al*. (2021) presents a theoretical model comprising customers' evaluation of Airbnb experiences (cognitive), emotional responses (affective) and loyal behaviour (conative) to understand customer lodging experience. The framework was also proved useful in understanding consumer acceptance of service innovations (e.g., Cao *et al*., 2022; Qin *et al*., 2021).

Based on Huang *et al*. (2021), this study focuses on cuteness, interactivity, coolness, courtesy, utility, and autonomy as cognitive evaluations, and positive affect (including satisfaction, novelty, and enjoyment) and negative affect as affective responses. The qualitative study by Huang *et al*. (2021) was conducted with a robust process of analysing a large amount of data (1145 online reviews). The cognitive evaluations and emotions identified in their study were frequently mentioned real-world experiences in online reviews, reflecting the reality of actual consumer responses to service robots. Huang *et al*. (2021) identified the perceived attributes (i.e., cognitive evaluations) of service robots to reflect both technological and social aspects of service robots, making it a solid base for the current study. Drawing on the cognitive-affective-conative framework (Bagozzi, 1992), this study proposes that different dimensions of cognitive evaluations of service robots induce consumers' positive and negative affect, which then influence their acceptance of service robots.

2.3 Hypotheses development

2.3.1 Effects of cuteness of service robots on consumers' positive and negative affect.

Cuteness relates to the extent to which the service robot is perceived to be cute and adorable (Huang *et al*., 2021). It is a childlike form of anthropomorphism (Lv *et al*., 2022). Cuteness can be viewed as consumers' positive evaluations of service robots, which produces positive emotional responses (Bagozzi, 1992). Studies have indicated that cuteness can activate brain pleasure systems and evoke feelings of being moved, touched, fun, and heart-warmed (Nenkov and Scott, 2014; Shin and Mattila, 2021). Lv *et al*. (2021) further verified that cuteness can stimulate tenderness—a form of positive affect. When interacting with service robots, these positive feelings may alleviate consumers' anxiety by creating a less intimidating and more approachable experience. Thus, we hypothesised that:

H1. The cuteness of service robots has a positive effect on consumers' positive affect (H1a), while having a negative effect on consumers' negative affect (H1b).

2.3.2 Effects of interactivity of service robots on consumers' positive and negative affect.

Interactivity refers to the perception that service robots can respond and facilitate communication (Huang *et al*., 2021). Favourable perceptions of interaction have been shown to increase consumers' delight and satisfaction (Ekinci and Dawes, 2009). Self-determination theory (Deci *et al*., 2017) assumes that people have an inherent psychological need for relatedness and being connected to and accepted by others. Meeting this need can result in more positive affect and effectively reduce emotional exhaustion (Deci *et al*., 2017; Ntoumanis *et al*., 2009). Service robots with a high level of perceived interactivity can elevate people's sense of relatedness, eventually leading to the formation of positive affect. Previous studies have demonstrated that the perceived high-quality interactivity of service robots leads to positive consumer affects (Selamat and Windasari, 2021). Conversely, a low-quality interactive system, characterised by a poorly designed interface or slow response speed, can negatively impact users' experience and willingness to use (Gao and Waechter, 2015). Accordingly, we proposed that:

H2. The interactivity of service robots has a positive effect on consumers' positive affect (H2a*)*, while having a negative effect on consumers' negative affect (H2b).

2.3.3 Effects of coolness of service robots on consumers' positive and negative affect. Coolness represents consumers' perception of robots as cool and cutting-edge (Huang *et al*., 2021). The use of modern technology can increase the perception of coolness (Liu and Mattila, 2019), which in turn may lead to satisfaction and subsequent adoption behaviours (Kim and Park, 2019). Previous literature has established the relationship between coolness and positive attitudes, affect and intention in general consumption and hosptality services (Cha, 2020; Im *et al*., 2015; Kim and Park, 2019). "Coolness" emphasises the "attractiveness, subcultural appeal and originality" (p. 179) of new devices (Sundar *et al*., 2014). As such, coolness can be considered as a positive perception of technological innovations, implying positive attitudes of consumers towards innovative products (Sundar *et al*., 2014). According to the cognitive-affective-conative framework (Bagozzi, 1992), coolness, as a positive evaluation of robots, may lead to positive consumer affect and alleviate discomfort triggered by uncertainty and threats in human-robot interactions. Therefore, we hypothesised that:

H3. The coolness of service robots has a positive effect on consumers' positive affect (H3a), while having a negative effect on consumers' negative affect (H3b).

2.3.4 Effects of courtesy of service robots on consumers' positive and negative affect. Courtesy refers to the expressions of employees to show their respect, friendliness and consideration to customers, which contributes to enhancing customers' service experience. (Gotlieb *et al*., 2004). When employees serve with a smile and make eye contact and friendly communication with customers, customers will experience a more positive emotional response (Li *et al*., 2016). Courtesy is a fundamental social norm in interpersonal communication, essential for fostering positive relationships between people (Bargiela-Chiappini, 2003). When treated courteously, customers feel valued and respected, and their self-esteem may be enhanced (Mruk, 2006). Furthermore, courtesy can be a useful tool in restoring customer satisfaction after a service failure (Hocutt and Stone, 1998). Therefore, being treated courteously by a robot may also put consumers in a positive emotional state. Research have shown that robots programmed with courteous attributes can lead to a better overall experience for uers (e.g., Lee *et al*., 2021). Thus, we proposed that:

H4. The courtesy of service robots has a positive effect on consumers' positive affect (H4a), while having a negative effect on consumers' negative affect (H4b).

2.3.5 Effects of utility of service robots on consumers' positive and negative affect.
Utility indicates users' perceived usefulness and instrumentality of products, enabling users to accomplish tasks more efficiently (Davis, 1989). Utility or related concepts are always considered as core variables in technology acceptance models (e.g., TAM, UTAUT, sRAM, AIDUA). Technology attraction theory suggests that effective technology can strengthen the relationships between consumers and service providers, forming positive evaluations and emotional connections (Zheng *et al*., 2020). Thus, the utility of service robots plays a crucial role in eliciting positive affect throughout the service process (Lin *et al*., 2019). We hypothesised that:

H5. The utility of service robots has a positive effect on consumers' positive affect (H5a), while having a negative effect on consumers' negative affect (H5b).

2.2.6 Effects of autonomy of service robots on consumers' positive and negative affect.
Autonomy refers to the degree to which a service robot can sense and perform tasks without direct human intervention (Huang *et al*., 2021). The autonomy of robots mainly depends on their control capacity, interaction accessibility and situation awareness (Riano *et al*., 2011) to independently sense and cope with changes in the environment (Jia *et al*., 2021). Service robots are usually equipped with autonomous control systems and communication capabilities to navigate the workplace and understand consumer needs (Tung and Au, 2018). Autonomy is essential to the anthropomorphism of robots (Epley *et al*., 2007) and has a positive impact on consumer affect (Blut *et al*., 2021). Autonomy can also reduce consumers' effort expectancy, leading to positive customer emotions (Gursoy *et al*., 2019). Therefore, we argue that perception of automation will lead to positive customer emotions and suppress negative customer emotions (Riano *et al*., 2011; Schepers *et al*., 2022). Accordingly, we proposed that:

H6. The autonomy of service robots has a positive effect on consumers' positive affect (H6a), while having a negative effect on consumers' negative affect (H6b).

2.3.7 Effects of positive affect and negative affect on consumers' acceptance of service robots.
Huang *et al*. (2021) found that consumers experienced three main positive affects during human-robot interactions: satisfaction, enjoyment and novelty. Consumer satisfaction is crucial in the service industry as satisfied consumers are more willing

to use the same service again (Ryu *et al*., 2012). Enjoyment is an influencing factor for consumer technology acceptance (e.g., Cha, 2020). Novelty, which is associated with emotional experience such as surprise and the "wow effect" (Fuentes-Moraleda *et al*., 2020), is also positively related to intentions to use technologies (Fazal-e-Hasan *et al*., 2021). Positive affect strongly predicts customer technology acceptance (e.g., Cao *et al*., 2022; Lu *et al*., 2019). However, negative affect can also arise after consumers' cognitive appraisal of service robots, leading consumers to employ coping strategies such as avoidance (Gao and Kerstetter, 2018; Xu *et al*., 2021). We thus hypothesised that:

H7. Consumers' positive affect has a positive effect on consumers' intention to use service robots.

H8. Consumers' negative affect has a negative effect on consumers' intentions to use service robots.

The conceptual model is shown in Figure 1.

--- Insert Figure 1 about here ---

3. **Methodology**

This study employed a mixed-method research design. As service robots in hospitality and tourism are an emerging phenomenon, and the cognitive and affective variables identified by Huang *et al*. (2021) lack a solid measurement scale, the mixed-method design is appropriate for this study to develop measurement and test hypotheses. This study involves two phases. Phase 1 developed measurement based on a literature review, interviews and a quantitative survey. Phase 2 tested the research hypotheses using a quantitative survey approach.

3.1 Phase 1. Measurement development

The measurement items for cognitive evaluations and affective responses were generated through a combination of existing literature and in-depth interviews. Twelve participants who had experience with service robots in hospitality and tourism settings were interviewed. The interviews were conducted by asking participants about their experiences with service robots and whether they had any perceptions of service robots (e.g., courtesy and cuteness) and affective responses (e.g., enjoyment and satisfaction) towards service robots. If they mentioned any related construct in the study, they were asked to elaborate on the feelings they have experienced. The interviews were conducted via audio calls, each lasting between 15 minutes and 32 minutes. All interviews were digitally recorded and transcribed with the participants' consent.

To analyse the interview data, the researchers used a qualitative content analysis approach with a deductive process (Elo and Kyngäs, 2008). They established a coding book based on the constructs created by Huang *et al*. (2021), which includes cuteness, interactivity, coolness, courtesy, utility, autonomy, satisfaction, novelty, enjoyment, and negative affect. The researchers then identified items from the interview data that fit within the constructs listed in the coding book. The quotes from the study by Huang *et al*. (2021) were also incorporated as items. Afterwards, a literature review was conducted to identify the measurement items for the constructs, which were adapted to the service robot context. In total, 51 items were identified (Appendix A).

The generated items were incorporated into a questionnaire using a 7-point Likert scale. A sociodemographic section was included in the questionnaire. The items were reviewed by four tourism researchers, who discussed the suitability and phrasing of the items repeatedly until they came to a consensus. A pre-test was then performed with 15 participants who had experienced service robots in hotels/restaurants. They pointed out problems with the items and gave suggestions for amendments. The questionnaire was adjusted accordingly.

A survey using purposive sampling was conducted to purify the measurement items. Sina Weibo (a social media platform) users who had experienced service robots in hospitality settings were invited to complete the survey. One of the researchers entered the keywords “hotel/restaurant” and “robot” in Sina Weibo to find experienced users based on the content of their posted reviews. The study invitations were sent to the selected users and those who agreed to participate in the study filled in the questionnaire. Furthermore, participants who had the experience were also recruited from the researchers’ social media and personal network. Three attention check questions were inserted into the questionnaire to ensure the quality of the responses. Finally, 109 valid responses were collected and analysed using IBM SPSS Statistics 27.

Exploratory factor analyse (EFA) was conducted using Varimax rotation method respectively to explore the dimensionality of scales for cognitive evaluations and affective responses respectively. The eigenvalue criterion for determining the number of factors is greater than 1.0 (Kaiser, 1960). The Kaiser–Meyer Olkin (KMO) value of cognitive evaluations is 0.872 and the KMO value of affective responses is 0.913, and their chi-square values in the Bartlett’s test of sphericity were significant at the 0.01 level, indicating that the data were suitable for factor analysis. After one item (“The service robot was stylish”) was deleted due to a cross loading issue (>0.50), EFA results supported the six-factor structure of cognitive evaluations and the four-factor structure of affective responses, which explain 82.176% and 85.980% of the total variance in the data, respectively. The Cronbach’s alpha values of all variables are above the recommended threshold of 0.7. Thus, the measurement scale has good structural reliability and internal consistency.

3.2 Phase 2. Data collection and analysis

In Phase 2, the measurement for cognitive evaluations and affective responses developed in the Phase 1 was used. The items ("I wish to be served by a service robot," "I am willing to be served by a service robot," "Overall, I strongly desire to be served by a service robot") for intention to use service robots was adapted from Tzou and Lu (2009). Data were collected through an online panel company Wenjuanxing (www.wjx.cn), with respondents receiving compensation of about US$2 for their participations. Respondents had to meet the criteria of having used service robots in hotels or restaurants. The same three attention check questions used in Phase 1 were utilised in the questionnaire. Finally, 450 valid questionnaires were collected. Table I shows the demographic characteristics of the sample. For data analysis, this study used partial least squares structural equation modelling (PLS-SEM), aided by Smart PLS 3. Compared with covariance-based (CB) SEM, PLS-SEM is more appropriate for exploratory study, capable of analysing both reflective and formative indicators, dealing with complex structural model effectively, and requiring a smaller sample size with fewer normality restrictions of data (Hair *et al*., 2011).

--- Insert Table I about here ---

4. Results

4.1 Common method bias

The Harman's single-factor test (Podsakoff *et al*., 2003) was applied to evaluate the presence of common method bias. The results show that a single factor explained only 26.217% of the variance which was below the threshold of 50%, indicating that the data were free from common method bias.

4.2 Measurement model test

After conducting the measurement model test, four items (see note in Appendix A) were deleted as removing them help improve the reliability and validity of related constructs (Hair *et al*., 2017). The remaining items were evaluated for reliability, convergent validity and discriminant validity (Appendix A). Cronbach's α and composite reliability values for all constructs were above the suggested cut-off value (0.7), indicating internal consistency reliability. All factor loadings were above 0.6 and the values of average variance extracted (AVE) exceeded the minimum threshold of 0.5 (Fornell and Larcker, 1981), satisfying the convergent validity. As shown in Table II, the square root of AVE for one construct is greater than its correlations with other constructs, confirming the discriminant validity (Fornell and Larcker, 1981).

--- Insert Table II about here ---

Formative measurement models are appropriate when indicators are not interchangeable and represent independent causes of the construct (Hair *et al*., 2017; Petter *et al*., 2007). Accordingly, the positive affect was treated as a second-order formative construct because the three dimensions (enjoyment, novelty and satisfaction) explored by this study are not interchangeable and they capture different aspects of the positive affect. Table III shows that all VIF values of the indicators for positive affect are less than 5, indicating collinearity is not an issue. The outer weights of the three indicators are significant at the 0.001 level, suggesting that all indicators should to be retained (Hair *et al*., 2017). As for the model fit information, the SRMR value of the measurement model (0.063) indicates a good fit, as it is below the threshold of 0.08 (Hair *et al*., 2017).

--- Insert Table III about here ---

4.3 Structural model test

The hypotheses were tested using the bootstrapping method with 5000 re-sampling. Table IV presents the results. H2a, H3a and H5a were not supported. The results indicate that interactivity had a positive effect on consumers' negative affect， contradicting H2b, while negative affect had a positive effect on intention to use, contradicting H8. The remaining nine hypotheses were supported. Table IV also shows the effect size (f^2) of each relationship. According to Chin (1998), the f^2 value varies from 0.02, 0.15, to 0.35, respectively indicating small, medium, and large effect sizes.

A higher coefficient of determination (R^2 value) indicates higher predictive accuracy. Chin (1998) suggests that R^2 values of 0.19, 0.33, and 0.67 in PLS-SEM path models indicate weak, moderate, and substantial predictive power, respectively. According to the R^2 value shown in Figure 2, the structural model explained 63.7% of the variance in positive affect, 20.7% in negative affect, and 40.6% in intention to use. The Q^2 values (Figure 2) being greater than zero indicate that the structural model has predictive relevance (Geisser, 1974; Stone, 1974).

--- Insert Table IV about here ---

--- Insert Figure 2 about here ---

5. Conclusion and Discussion

This study proposed and verified a model of consumer acceptance of service robots in hospitality based on the cognitive-affective-conative framework. According to the research by Huang *et al*. (2021), the model included cognitive dimensions (cuteness, interactivity, coolness, courtesy, utility, and autonomy), positive affect (including enjoyment, novelty, and satisfaction), and negative affect, providing a comprehensive understanding of the influencing factors and underlining mechanisms of consumer intention to use service robots.

5.1 Discussion

The study findings revealed that cuteness and courtesy, as anthropomorphic features of service robots, played a significant role in forming consumer positive affect and reducing negative affect. Similarly, utility, as functional attributes, were found to matter in fostering positive affect. Thus, this study confirms that service robots' anthropomorphic features and functional attributes jointly shape customer affective experience in customer-robot interactions, implying that cute appeal as aesthetic value and "respect" expressed through "courtesy" have to build in addition to the functional attributes to engage consumers. The findings resonate with the call for understanding customer-robot interactions by integrating both anthropomorphic (e.g., cuteness and courtesy) and intelligent (e.g., autonomy and utility) features as two fundamental design properties (Moussawi *et al*., 2021).

The findings revealed that the influence of interactivity on positive affect was insignificant, aligning a study on digital voice assistants by Fernandes and Oliveira (2021). Surprisingly, this study also found that interactivity led to negative affect. This unexpected finding can be explained by considering that higher level of interactivity may threaten consumers' human identity. Communication and interaction are seen as distinctive human features and essential aspect of social existence (Pelau *et al*., 2021). The interactivity of service robots, which may resemble human features, could trigger a feeling of discomfort, eeriness and a perceived threat to human identity, as suggested by the uncanny valley theory (Mori *et al*., 2012) and the study by Mende *et al*. (2019). Thus, it is reasonable to observe negative affect arising from interactivity in human-robot interactions.

The finding that negative affect positively influences consumers' intention to use service robots is interesting, contradicting previous literature on human-human interactions (e.g., Jung and Yoon, 2011). Two explanations can be considered. First, fear, the main negative affect in real-world human-robot interactions (Huang *et al*., 2021), may be connected to enjoyment and curiosity per the "enjoyment of fear" (Hitchcock, 1949) and the "paradox of horror" proposed by Carroll (2003) who claimed that "horror attracts because anomalies command attention and elicit curiosity" (p. 195). People may enjoy fear since the curiosity triggered by fear can serve as "an appetite of the mind" (Carroll, 2003, p. 184) that leads to consumers' intention to use service robots. Secondly, individuals have the ability to cope with negative affect using internal and external resources (Lazarus, 1991). Therefore, the negative affect stimulated by interacting with service robots may fall within consumers' ability to manage it. They thus accept service robots even they have experienced a negative feeling.

5.2 Theoretical implications

This study contributes to the literature in several ways. First, drawing on the cognitive-affective-conative framework, this study adds to the understanding of service robot acceptance by testing a holistic model that considers both cognitive evaluations and affective responses to actual human-robot interactions. While previous studies have identified different antecedents of consumer acceptance, there is a lack of holistic models that integrate cognitive appraisals and associated emotions (Schepers *et al*., 2022; Zhang *et al*., 2021). Thus, this study contributes to expanding theoretical perspectives and improving our understanding of consumer acceptance behaviour. Additionally, unlike previous studies that relied on video or photo stimuli to inform participants about robots (e.g., Liu *et al*., 2022), this study provides valuable insights by field-testing consumer actual responses, thereby contributing to a more detailed acceptance model from a cognitive-affective-conative perspective.

Second, this study contributes to the understanding of humanness cues in service robot acceptance. While recent research has highlighted the importance of humanness cues, including social capability, appearance, and competence in facilitating human-robot interactions (e.g., Belanche *et al*., 2021; Song and Kim, 2022; Zhang *et al*., 2022), this study provides more nuanced insights (including cuteness, interactivity, coolness, courtesy, utility, and autonomy) into consumer evaluation of cues related to humanness. For instance, courtesy and interactivity provide a more detailed reflection of social capability, while autonomy and utility reflect the competence of service robots. This study also validates the measurement of these constructs, laying a foundation for future research interested in exploring humanness cues.

Third, this study deconstructs the psychological mechanisms of consumer acceptance by considering both positive and negative affect, echoing Tuomi *et al*.'s (2021) findings on the importance of psychological factors in adopting service robots in hospitality. As affective responses are an important element elicited in human-robot interactions, researchers have suggested that including an emotional perspective can provide a more comprehensive understanding of consumer behavioural intentions toward service robots (Schepers *et al*., 2022; Song and Kim, 2022). In response to this call, this study reveals that positive and negative affect can influence consumer intention to use service robots, providing novel insights into customer-robot interaction research. This study agrees with previous literature that consumers in hospitality settings can have mixed responses to service robots, including both positive and negative reactions (Akdim *et al*., 2021). While negative affect in customer-robot interactions is typically seen as undesirable, this study argues that not all negative affect should be avoided. People can be novelty seekers who enjoy satisfying their curiosity in a horror situation (Carroll, 2003) and they may be capable of managing negative affect triggered by customer-robot interactions.

5.3 Practical implications

This study provides significant implications for the design and implementation of service robots in the hospitality and tourism sector. As consumer attitudes towards robots are possibly associated with their willingness-to-pay for hospitality and tourism services (Ivanov and Webster, 2021), business managers and robot designers can apply strategies that consider both cognitive evaluations and affective responses explored by this study to facilitate consumer acceptance of service robots.

Both positive and negative affect have implications in the design and implementation of service robots. The results of this study show that positive affect (f^2=0.633) has larger effect size than negative affect (f^2=0.010) on consumer acceptance intention (Table IV), indicating that stimulating consumer positive affect would be a more effective way to improve consumer acceptance. Thus, it is vital to ensure that service robots can engage customers with positive affect, such as feelings of novelty, satisfaction and enjoyment. While negative affect accompanied by curiosity may have some potential benefits, caution should be exercised, and further research is needed to understand the specific types and levels of negative affect that can be helpful in customer-robot interactions.

This study identified five significant factors contributing to positive emotions among customers: utility, cuteness, coolness, courtesy, and autonomy. Leveraging these attributes can help engage consumers with value-added experiences in the hospitality industry. According to Table IV, utility (f^2=0.148) has the strongest effect size among the factors, indicating that perceiving service robots as useful, practical, efficient, convenient, and helpful leads to positive emotions. Autonomy is also important for positive affect, highlighting the need for robots to perform functional tasks autonomously. Therefore, managers should prioritize employing service robots that provide efficient and useful services to customers, avoiding their use as mere gimmicks.

Customers highly value the cuteness and coolness of service robots. To meet these preferences, robot designers should focus on the aesthetic design, vocal qualities, and communication skills that enhance robots' cuteness and coolness. The significant role of courtesy in shaping customers' positive affect provides empirical evidence for the computers as social actors (Nass *et al*., 1994) in the customer-robot interaction context, suggesting that service robots should be designed as social actors that adhere to social rules and norms.

In addition to identifying the factors influencing customers affect and acceptance, this study also provides a measurement tool for customer cognitive evaluations of service robots. Managers can use this tool to assess robot performance and make informed decisions about investing in service robots with desirable attributes that can improve customer emotional experiences in the hospitality and tourism industry.

5.4 Limitations and future research

Several limitations need to be acknowledged. First, this study only focuses on the determining role of cognition in emotion, neglecting the bidirectional relationship between cognitive activity and emotions as discussed by Lazarus (1991). The role of cognitive activity in emotion is contingent upon where researchers make their observations. Exploring how consumer affective responses influence cognitive evaluations in human-robot evaluations would be a valuable area for future research. Second, this study regarded negative affect as a single dimension, overlooking the multi-dimensional nature of negative affect. Future research could examine the distinct roles of specific negative affect, such as anxiety, annoyance, and anger.

References

Akdim, K., Belanche, D. and Flavián, M. (2021), "Attitudes toward service robots: analyses of explicit and implicit attitudes based on anthropomorphism and construal level theory", *International Journal of Contemporary Hospitality Management*.

Bagozzi, R. P. (1992), "The self-regulation of attitudes, intentions, and behavior", *Social Psychology Quarterly*, Vol. 55 No. 2, pp. 178-204, doi: 10.2307/2786945.

Bargiela-Chiappini, F. (2003), "Face and politeness: new (insights) for old (concepts)", *Journal of Pragmatics*, Vol. 35 No. 10-11, pp.1453-1469.

Belanche, D., Casaló, L. V. and Flavián, C. (2019), "Artificial intelligence in FinTech: understanding robo-advisors adoption among customers", *Industrial Management & Data Systems*, Vol. 119 No. 7, pp. 1411-1430, doi: 10.1108/imds-08-2018-0368.

Belanche, D., Casaló, L. V. and Flavián, C. (2020a), "Frontline robots in tourism and hospitality: service enhancement or cost reduction?", *Electronic Markets,* pp. 1-16, doi: 10.1007/s12525-020-00432-5.

Belanche, D., Casaló, L.V., Flavián, C. and Schepers, J. (2020b), "Robots or frontline employees? Exploring customers' attributions of responsibility and stability after service failure or success", *Journal of Service Management*, Vol. 31 No. 2, pp. 267-289.

Belanche, D., Casaló, L.V., Flavián, C. and Schepers, J. (2020c), "Service robot implementation: a theoretical framework and research agenda", *The Service Industries Journal*, Vol. 40 No. 3-4, pp. 203-225.

Belanche, D., Casaló, L.V., Schepers, J. and Flavián, C. (2021), "Examining the effects of robots' physical appearance, warmth, and competence in frontline services: The Humanness-Value-Loyalty model", *Psychology & Marketing*, Vol. 38 No. 12, pp. 2357-2376.

Blut, M., Wang, C., Wünderlich, N.V. and Brock, C. (2021), "Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI", *Journal of the Academy of Marketing Science*, Vol. 49, pp. 632-658.

Boo, H.C. and Chua, B.L. (2022), "An integrative model of facial recognition check-in technology adoption intention: the perspective of hotel guests in Singapore", *International Journal of Contemporary Hospitality Management*.

Byrd, K., Fan, A., Her, E., Liu, Y., Almanza, B. and Leitch, S., (2021), "Robot vs human: expectations, performances and gaps in off-premise restaurant service modes", *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 11, pp. 3996-4016.

Cai, R., Cain, L.N. and Jeon, H. (2022), "Customers' perceptions of hotel AI-enabled voice assistants: does brand matter?", *International Journal of Contemporary Hospitality Management*.

Cao, Y. Y., Qin, X. H., Li, J. J., Long, Q. Q. and Hu, B. (2022), "Exploring seniors' continuance intention to use mobile social network sites in China: a cognitive-affective-conative model", *Universal Access in the Information Society*, Vol. 21 No. 1, pp. 71-92, doi: 10.1007/s10209-020-00762-3.

Carroll, N. (2003), *The philosophy of horror: or, paradoxes of the heart*, Routledge.

Cha, S. S. (2020), "Customers' intention to use robot-serviced restaurants in Korea: relationship of coolness and MCI factors", *International Journal of Contemporary Hospitality Management*, Vol. 32 No. 9, pp. 2947-2968, doi: 10.1108/IJCHM-01-2020-0046.

Chi, O. H., Gursoy, D. and Chi, C. G. (2020), "Tourists' attitudes toward the use of artificially intelligent (AI) devices in tourism service delivery: moderating role of service value seeking", *Journal of Travel Research*, Vol. 61 No. 1, pp. 170-185, doi: 10.1177/0047287520971054.

Chin, W. W. (1998), "The partial least squares approach to structural equation modeling", in Marcoulides, G. A. (Ed.), *Modern Methods for Business Research*, Lawrence Erlbaum Associates, Mahwah, NJ, pp. 259-358.

Davis, F. D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly: Management Information Systems*, Vol. 13 No. 3, pp. 319-339, doi: 10.2307/249008.

Deci, E. L., Olafsen, A. H. and Ryan, R. M. (2017), "Self-determination theory in work organizations: the state of a science", *Annual Review of Organizational Psychology and Organizational Behavior*, Vol. 4, pp. 19-43.

Elo, S. and Kyngäs, H. (2008), "The qualitative content analysis process", *Journal of Advanced Nursing*, Vol. 62 No. 1, pp. 107–115.

Ekinci, Y. and Dawes, P. L. (2009), "Consumer perceptions of frontline service employee personality traits, interaction quality, and consumer satisfaction", *Service Industries Journal*, Vol. 29 No. 4, pp. 503-521, doi: 10.1080/02642060802283113.

Epley, N., Waytz, A. and Cacioppo, J.T. (2007), "On seeing human: a three-factor theory of anthropomorphism", *Psychological Review*, Vol. 114 No. 4, pp. 864–886.

Fazal-e-Hasan, S. M., Amrollahi, A., Mortimer, G., Adapa, S. and Balaji, M. S. (2021), "A multi-method approach to examining consumer intentions to use smart retail technology", *Computers in Human Behavior*, Vol. 117. doi: 10.1016/j.chb.2020.106622.

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.

Flavián, C. and Casaló, L.V. (2021), "Artificial intelligence in services: current trends, benefits and challenges", *The Service Industries Journal*, Vol. 41 No. 13-14, pp.853-859.

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.

Fortune. (2020), "Service robotics market size, share and COVID-19 impact analysis", available at: https://www.fortunebusinessinsights.com/industry-reports/service-robotics-market-101805 (assessed 4 August 2022)

Fu, S., Zheng, X. and Wong, I. A. (2022), "The perils of hotel technology: the robot usage resistance model", *International Journal of Hospitality Management*, Vol. 102, p. 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, doi: 10.1016/j.tmp.2020.100751.

Gao, J. and Kerstetter, D. L. (2018), "From sad to happy to happier: emotion regulation strategies used during a vacation", *Annals of Tourism Research*, Vol. 69, pp. 1-14.

Gao, L. and Waechter, K. A. (2015), "Examining the role of initial trust in user adoption of mobile payment services: an empirical investigation", *Information Systems Frontiers*, Vol. 19 No. 3, pp. 525-548, doi: 10.1007/s10796-015-9611-0.

Geisser, S. (1974), "A predictive approach to the random effect model", *Biometrika*, Vol. 61 No. 1, pp. 101-107, doi: 10.1093/biomet/61.1.101.

Gotlieb, J., Levy, M., Grewal, D. and Lindsey-Mullikin, J. (2004), "An examination of moderators of the effects of customers' evaluation of employee courtesy on attitude toward the service firm 1", *Journal of Applied Social Psychology*, Vol. 34 No. 4, pp. 825-847.

Guan, X., Gong, J., Li, M. and Huan, T.-C. (2022), “Exploring key factors influencing customer behavioral intention in robot restaurants”, *International Journal of Contemporary Hospitality Management*, Vol. 34 No. 9, pp. 3482-3501.

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., Hult, G. T. M., Ringle, C. M. and Sarstedt, M. (2017), *A primer on partial least squares structural equation modeling (PLS-SEM)*, 2nd ed., SAGE, Los Angeles.

Hair, J. F., Ringle, C. M. and Sarstedt, M. (2011), “PLS-SEM: indeed a silver bullet”, *Journal of Marketing Theory and Practice*, Vol. 19 No. 2, pp. 139-152, doi: 10.2753/MTP1069-6679190202

Hitchcock, A. (1949), “The enjoyment of fear”, *Good Housekeeping*, Vol. 39, pp. 241-243.

Hocutt, M. A. and Stone, T. H. (1998), “The impact of employee empowerment on the quality of a service recovery effort”, *Journal of Quality Management*, Vol. 3 No. 1, pp. 117-132.

Hu, Q., Lu, Y., Pan, Z., Gong, Y. and Yang, Z. (2021), “Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants”, *International Journal of Information Management*, Vol. 56, doi: 10.1016/j.ijinfomgt.2020.102250

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

Im, S., Bhat, S. and Lee, Y. (2015), “Consumer perceptions of product creativity, coolness, value and attitude”, *Journal of Business Research*, Vol. 68 No. 1, pp. 166-172, doi: 10.1016/j.jbusres.2014.03.014

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.

Ivanov, S. and Webster, C. (2019), “Robots in tourism: a research agenda for tourism economics”, *Tourism Economics*, Vol. 26 No. 7, pp. 1065-1085, doi: 10.1177/1354816619879583

Ivanov, S., and Webster, C. (2021), “Willingness-to-pay for robot-delivered tourism and hospitality services–an exploratory study”, *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 11, pp. 3926-3955

Ivanov, S., Webster, C. and Berezina, K. (2022). “Robotics in tourism and hospitality”, *Handbook of e-Tourism*, pp. 1873-1899.

Jia, J. W., Chung, N. and Hwang, J. (2021). “Assessing the hotel service robot interaction on tourists' behaviour: the role of anthropomorphism”, *Industrial Management & Data Systems*.

Jung, H. S. and Yoon, H. H. (2011), “The effects of nonverbal communication of employees in the family restaurant upon customers' emotional responses and customer satisfaction”, *International Journal of Hospitality Management*, Vol. 30 No. 3, pp. 542-550, doi: 10.1016/j.ijhm.2010.09.005

Kaiser, H. F. (1960), “The application of electronic computers to factor analysis”, *Educational and Psychological Measurement*, Vol. 20 No. 1, pp. 141-151, doi: 10.1177/001316446002000116

Khoa, D.T., Gip, H.Q., Guchait, P. and Wang, C.-Y. (2023), “Competition or collaboration for human–robot relationship: a critical reflection on future cobotics in hospitality”, *International Journal of Contemporary Hospitality Management*, Vol. 35 No. 6, pp. 2202-2215.

Kim, H., So, K. K. F. and Wirtz, J. (2022), “Service robots: applying social exchange theory to better understand human–robot interactions”, *Tourism Management*, Vol. 92, p. 104537.

Kim, J. and Park, E. (2019), “Beyond coolness: predicting the technology adoption of interactive wearable devices”, *Journal of Retailing and Consumer Services*, Vol. 49, pp. 114-119, doi: 10.1016/j.jretconser.2019.03.013

Kim, J. H., Ritchie, J. R. B. and McCormick, B. (2012), “Development of a scale to measure memorable tourism experiences”, *Journal of Travel Research*, Vol. 51 No. 1, pp. 12-25, doi: 10.1177/0047287510385467

Law, R., Ye, H. and Chan, I.C.C. (2022), “A critical review of smart hospitality and tourism research”, *International Journal of Contemporary Hospitality Management*, Vol. 34 No. 2, pp. 623-641.

Lazarus, R. S. (1991), *Emotion and adaptation*, Oxford University Press, New York.

Lazarus, R. S. and Folkman, S. (1984), *Stress, appraisal, and coping*, Springer publishing company, New York.

Lee, J. G., Lee, J. and Lee, D. (2021), “Cheerful encouragement or careful listening: the dynamics of robot etiquette at Children's different developmental stages”, *Computers in Human Behavior*, Vol. 118, p.106697, doi: 10.1016/j.chb.2021.106697

Li, J., Canziani, B. and Hsieh, Y. (2016), “US and Chinese perceptions of simulated US courtesy”, *Worldwide Hospitality and Tourism Themes*, Vol. 8 No. 1, pp. 29-40, doi: 10.1108/WHATT-10-2015-0035

Li, J., Hudson, S. and So, K. K. F. (2021), “Hedonic consumption pathway vs. acquisition-transaction utility pathway: an empirical comparison of Airbnb and hotels”, *International Journal of Hospitality Management*, Vol. 94. doi: 10.1016/j.ijhm.2020.102844

Lin, H., Chi, O.H. and Gursoy, D. (2020), “Antecedents of customers’ acceptance of artificially intelligent robotic device use in hospitality services”, *Journal of Hospitality Marketing & Management*, Vol. 29 No. 5, pp.530-549.

Liu, S. Q. and Mattila, A. S. (2019), “Apple Pay: coolness and embarrassment in the service encounter”, *International Journal of Hospitality Management*, Vol. 78, pp. 268-275, doi: 10.1016/j.ijhm.2018.09.009

Liu, X. S., Yi, X. S. and Wan, L. C. (2022), “Friendly or competent? The effects of perception of robot appearance and service context on usage intention”, *Annals of Tourism Research*, Vol. 92, doi: 10.1016/j.annals.2021.103324

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

Lv, X., Liu, Y., Luo, J., Liu, Y. and Li, C. (2021), “Does a cute artificial intelligence assistant soften the blow? The impact of cuteness on customer tolerance of assistant service failure”, *Annals of Tourism Research*, Vol. 87, doi: 10.1016/j.annals.2020.103114

Lv, X., Luo, J., Liang, Y., Liu, Y. and Li, C. (2022), “Is cuteness irresistible? The impact of cuteness on customers’ intentions to use AI applications”, *Tourism Management*, Vol. 90, doi: 10.1016/j.tourman.2021.104472

Mano, H. and Oliver, R. L. (1993), “Assessing the dimensionality and structure of the consumption experience: evaluation, feeling, and satisfaction”, *Journal of Consumer Research*, Vol. 20 No. 3, pp. 451-466, doi: 10.1086/209361

Mende, M., Scott, M. L., 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

Mori, M., MacDorman, K. F. and Kageki, N. (2012), “The uncanny valley”, *IEEE Robotics and Automation Magazine*, Vol. 19 No. 2, pp. 98-100. doi: 10.1109/MRA.2012.2192811

Moussawi, S., Koufaris, M. and Benbunan-Fich, R. (2021), “How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents”, *Electronic Markets,* Vol. 31 No. 2, pp. 343-364, doi: 10.1007/s12525-020-00411-w

Mruk, C.J. (2006), *Self-esteem research, theory, and practice: toward a positive psychology of self-esteem*, 3rd ed., Springer Publishing Company, New York.

Nass, C., Steuer, J. and Tauber, E. R. (1994), “Computer are social actors”, *Paper presented at the Conference on Human Factors in Computing Systems Proceedings*.

Nenkov, G. Y. and Scott, M. L. (2014), “'So cute I could eat it up': priming effects of cute products on indulgent consumption”, *Journal of Consumer Research,* Vol. 41 No. 2, pp. 326-341, doi: 10.1086/676581

Ntoumanis, N., Edmunds, J. and Duda, J.L. (2009), “Understanding the coping process from a self-determination theory perspective”, *British Journal of Health Psychology*, Vol. 14 No. 2, pp.249-260.

Ozdemir, O., Dogru, T., Kizildag, M. and Erkmen, E. (2023), “A critical reflection on digitalization for the hospitality and tourism industry: value implications for stakeholders”, *International Journal of Contemporary Hospitality Management*, Vol. ahead-of-print

Pelau, C., Dabija, D. C. and 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”, *Computers in Human Behavior*, Vol. 122, doi: 10.1016/j.chb.2021.106855

Petter, S., Straub, D. and Rai, A. (2007), “Specifying formative constructs in information systems research”, MIS Quarterly, pp. 623-656.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903.

Qin, H., Osatuyi, B. and Xu, L. (2021), “How mobile augmented reality applications affect continuous use and purchase intentions: a cognition-affect-conation perspective”, *Journal of Retailing and Consumer Services,* Vol. 63, doi: 10.1016/j.jretconser.2021.102680

Riano, L., Burbridge, C. and McGinnity, T. M. (2011), “A study of enhanced robot autonomy in telepresence”*, Paper presented at the Artificial Intelligence and Cognitive Systems*.

Romero, J. and Lado, N. (2021), “Service robots and COVID-19: exploring perceptions of prevention efficacy at hotels in generation Z”, *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 11, pp. 4057-4078.

Ruiz-Equihua, D., Romero, J., Loureiro, S.M.C. and Ali, M. (2022), “Human–robot interactions in the restaurant setting: the role of social cognition, psychological ownership and anthropomorphism”, *International Journal of Contemporary Hospitality Management*, Vol. 35 No. 6, pp.1966-1985.

Ryu, K., Lee, H. and Gon Kim, W. (2012), “The influence of the quality of the physical environment, food, and service on restaurant image, customer perceived value, customer satisfaction, and behavioral intentions”, *International Journal of Contemporary Hospitality Management*, Vol. 24 No. 2, pp. 200-223.

Sari, F. O., Bulut, C., & Pirnar, I. (2016), “Adaptation of hospitality service quality scales for marina services”, *International Journal of Hospitality Management,* Vol. *54*, pp. 95-103. doi: 10.1016/j.ijhm.2016.02.004

Schepers, J., Belanche, D., Casaló, L.V. and Flavián, C. (2022), “How smart should a service robot be?”, *Journal of Service Research*, Vol. 25 No. 4, pp. 565-582.

Selamat, M. A. and Windasari, N. A. (2021), “Chatbot for SMEs: integrating customer and business owner perspectives”, *Technology in Society*, Vol. 66. doi: 10.1016/j.techsoc.2021.101685

Shin, H. (2022), “A critical review of robot research and future research opportunities: adopting a service ecosystem perspective”, *International Journal of Contemporary Hospitality Management*. Vol. 34 No. 6, pp. 2337-2358

Shin, H. and Jeong, M. (2020), “Guests’ perceptions of robot concierge and their adoption intentions”, *International Journal of Contemporary Hospitality Management, Vol. 32* No. 8, pp. 2613-2633, doi: 10.1108/IJCHM-09-2019-0798

Shin, J. and Mattila, A. S. (2021), “Aww effect: engaging consumers in “non-cute” prosocial initiatives with cuteness”, *Journal of Business Research*, Vol. 126, pp. 209-220, doi: 10.1016/j.jbusres.2020.11.046

Song, C.S. and Kim, Y.K. (2022), “The role of the human-robot interaction in consumers’ acceptance of humanoid retail service robots”, J*ournal of Business Research*, Vol. 146, pp. 489-503.

Stone, M. (1974), “Cross-validatory choice and assessment of statistical predictions”. *Journal of Royal Statistical Society, Series B*, Vol. 36 No. 2, pp. 111-147, doi: 10.1111/j.2517-6161.1974.tb00994.x

Sundar, S. S., Tamul, D. J. and Wu, M. (2014), “Capturing 'cool': measures for assessing coolness of technological products”, *International Journal of Human Computer Studies*, Vol. 72 No. 2, pp. 169-180, doi: 10.1016/j.ijhcs.2013.09.008

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

Tuomi, A., Tussyadiah, I.P. and Hanna, P. (2021), “Spicing up hospitality service encounters: the case of Pepper™”, *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 11, pp. 3906-3925.

Tussyadiah, I. P. (2016), “Factors of satisfaction and intention to use peer-to-peer accommodation”, *International Journal of Hospitality Management*, Vol. 55, pp. 70-80, doi: 10.1016/j.ijhm.2016.03.005

Tzou, R. C. and Lu, H. P. (2009), “Exploring the emotional, aesthetic, and ergonomic facets of innovative product on fashion technology acceptance model”, *Behaviour and Information Technology*, Vol. 28 No. 4, pp. 311-322, doi: 10.1080/01449290701763454

Venkatesh, V. (2000), “Determinants of perceived ease of use: integrating control, intrinsic motivation, and emotion into the Technology Acceptance Model”, *Information Systems Research*, Vol. 11 No. 4, pp. 342-365, doi: 10.1287/isre.11.4.342.11872

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

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

Xu, X. (Even), Huang, D. and Chen, Q. (2021), “Stress and coping among micro-entrepreneurs of peer-to-peer accommodation”, *International Journal of Hospitality Management*, Vol. 97, doi:10.1016/j.ijhm.2021.103009

Zhang, M., Gursoy, D., Zhu, Z. and Shi, S. (2021), “Impact of anthropomorphic features of artificially intelligent service robots on consumer acceptance: moderating role of sense of humor”, *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 11, pp. 3883-3905, doi: 10.1108/IJCHM-11-2020-1256

Zhang, X., Balaji, M.S. and Jiang, Y. (2022), “Robots at your service: value facilitation and value co-creation in restaurants”, *International Journal of Contemporary Hospitality Management*, Vol. 34 No. 5, pp. 2004-2025.

Zheng, X., Men, J., Xiang, L. and Yang, F. (2020), “Role of technology attraction and parasocial interaction in social shopping websites”, *International Journal of Information Management*, Vol. 51, p.102043.

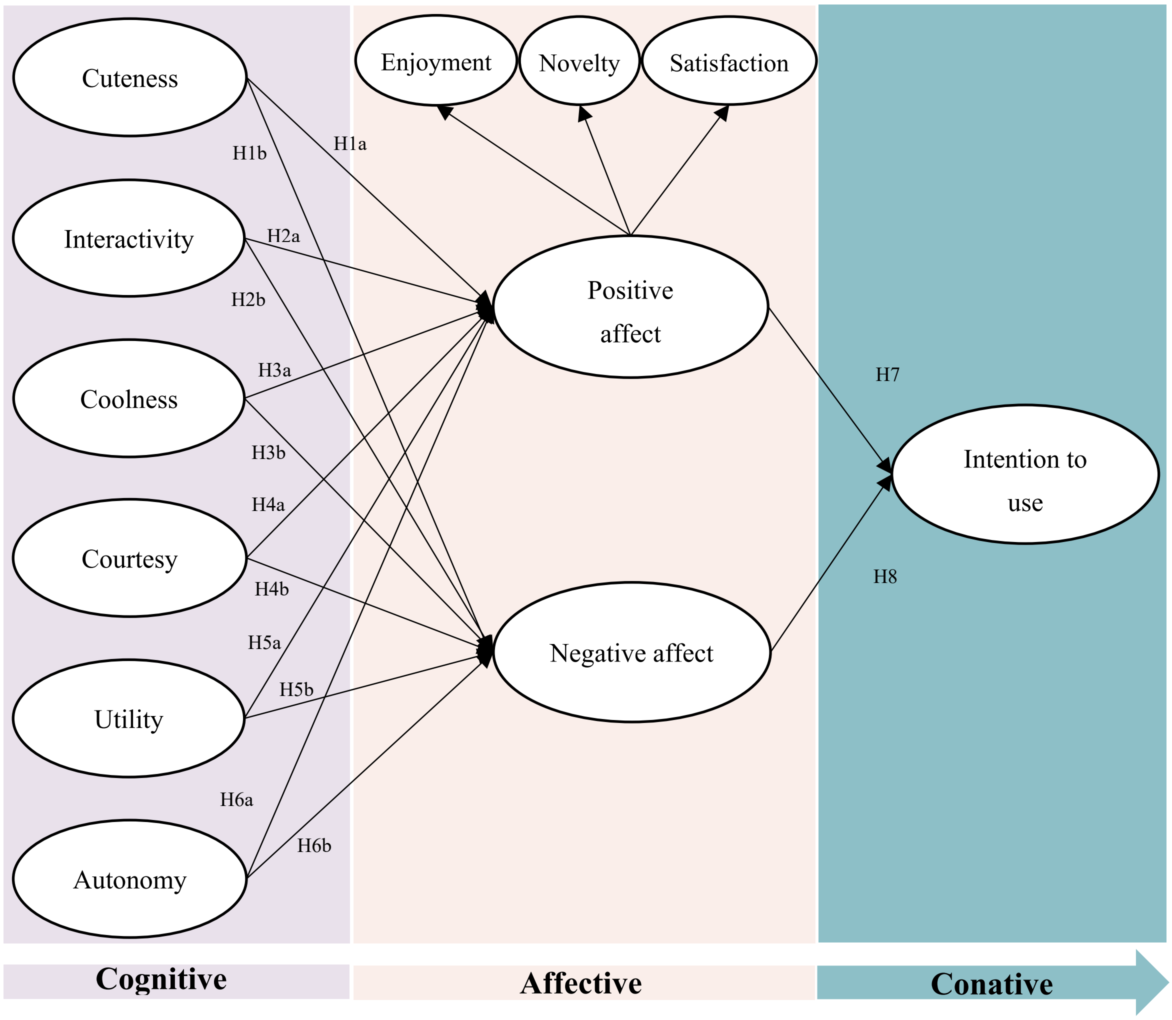
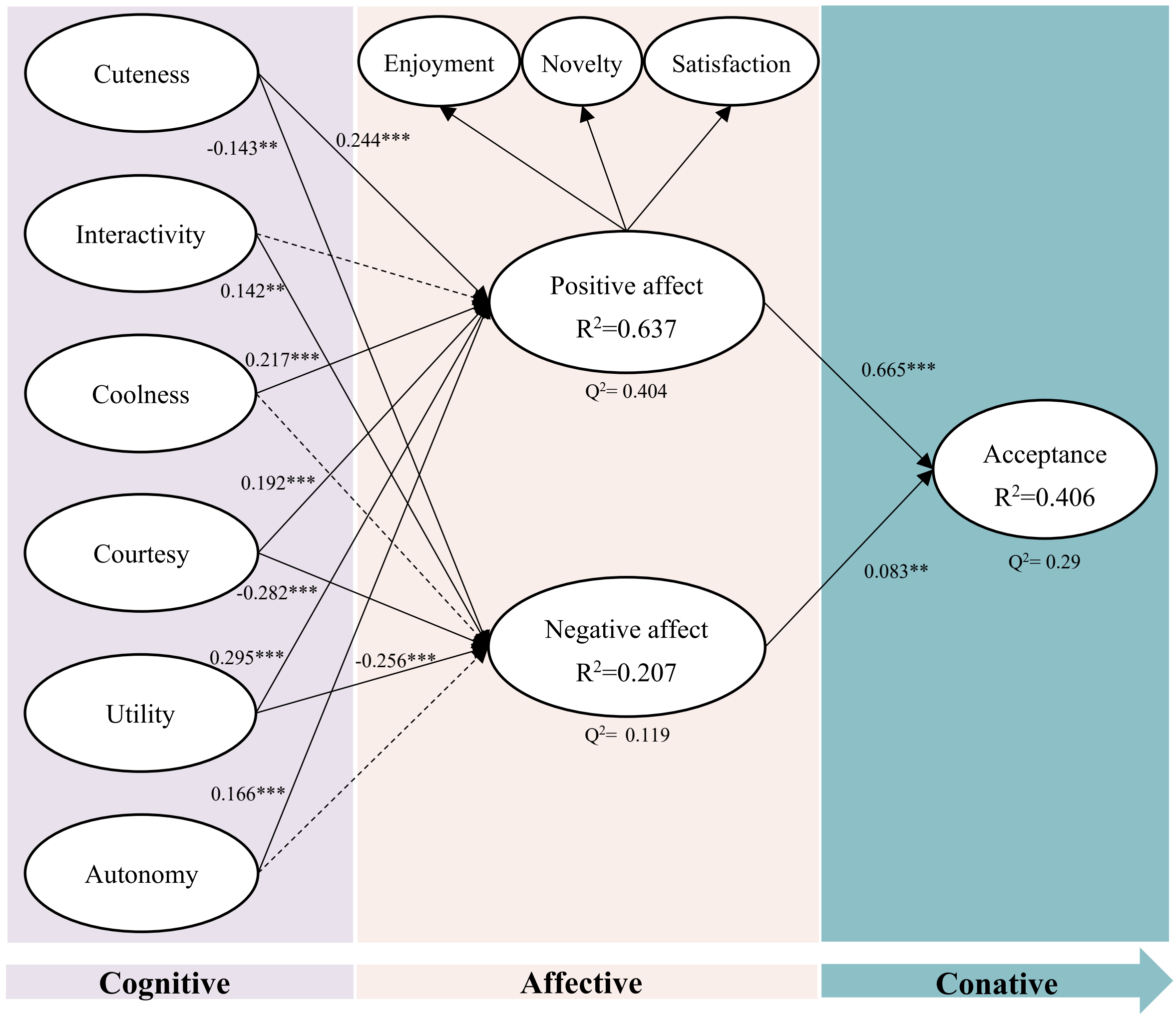


Figure 1. Conceptual model

Source: Created by author



Note: *** means p < 0.001, ** means p < 0.01, * means p < 0.05.

Figure 2. Results of structural equation modelling

Source: Created by author

Table I. Demographic profile (N = 450)

Measure	Items	Frequency	Percentage (%)
	Hotel	260	57.8
	Restaurant	190	42.2
Gender	Male	258	57.3
	Female	192	42.7
Age	18-25	84	18.7
	26-30	123	27.3
	31-40	191	42.4
	41-50	39	8.7
	Above50	13	2.9
Profession	Student	38	8.4
	Company staff	349	77.6
	Staff of Party, government or public institutions	47	10.4
	Others	16	3.6

Source: Created by author

Table II. Discriminant validity test

	IU	ENJ	NOV	SAT	AUT	COOL	COUR	CU	INT	NA	UTI
IU	**0.852**										
ENJ	0.450	**0.714**									
NOV	0.436	0.539	**0.737**								
SAT	0.599	0.504	0.446	**0.741**							
AUT	0.462	0.402	0.321	0.516	**0.801**						
COOL	0.422	0.491	0.472	0.497	0.430	**0.783**					
COUR	0.375	0.503	0.442	0.488	0.372	0.454	**0.734**				
CU	0.409	0.472	0.428	0.477	0.283	0.473	0.386	**0.761**			
INT	0.376	0.412	0.258	0.401	0.466	0.607	0.416	0.363	**0.801**		
NA	-0.174	-0.341	-0.284	-0.327	-0.164	-0.113	-0.358	-0.243	-0.056	**0.771**	
UTI	0.541	0.457	0.387	0.612	0.510	0.393	0.490	0.348	0.348	-0.355	**0.713**

Note: Diagonal elements represent the square root of the AVE values, others are correlation between constructs; IU = Intention to use; ENJ = enjoyment; NOV = Novelty; SAT = Satisfaction; AUT = Autonomy; COOL = Coolness; COUR = Courtesy; CU = Cuteness; INT = Interactivity; NA =Negative affect; UTI = Utility

Source: Created by author

Table III. Evaluation of second-order formative constructs

Second-order constructs	Indicators	VIF	Outer loading	Outer weights	P-value
Positive affect	Enjoyment	1.607	0.762	0.298	0.000
	Novelty	1.500	0.702	0.245	0.000
	Satisfaction	1.430	0.917	0.655	0.000

Source: Created by author

Table IV. Results of hypothesis testing

	Relationships	Path coefficient	T-value	P-value	f^2	Supported or not?
H1a	Cuteness→Positive affect	0.244***	6.058	0.000	0.119	Y
H1b	Cuteness→Negative affect	-0.143**	2.700	0.007	0.019	Y
H2a	Interactivity→Positive affect	-0.031	0.612	0.541	0.002	N
H2b	Interactivity→Negative affect	0.142**	2.703	0.007	0.014	N
H3a	Coolness→Positive affect	0.217***	4.555	0.000	0.068	Y
H3b	Coolness→Negative affect	0.096	1.795	0.073	0.006	N
H4a	Courtesy→Positive affect	0.192***	4.615	0.000	0.066	Y
H4b	Courtesy→Negative affect	-0.282***	5.587	0.000	0.065	Y
H5a	Utility→Positive affect	0.295***	6.300	0.000	0.148	Y
H5b	Utility→Negative affect	-0.256***	4.858	0.000	0.051	Y
H6a	Autonomy→Positive affect	0.166***	4.264	0.000	0.048	Y
H6b	Autonomy→Negative affect	0.005	0.087	0.930	0.000	N
H7	Positive affect→Intention to use	0.665***	17.774	0.000	0.633	Y
H8	Negative affect→Intention to use	0.083**	2.478	0.013	0.010	N

Note: *** means p < 0.001, ** means p < 0.01, * means p < 0.05.

Source: Created by author

Appendix A. Scale refinement

Construct and Items	Resource	Factor loading	Mean value
Utility α=0.758; CR=0.837; AVE=0.508			
The service robot was useful	Im *et al.* (2015)	0.724	5.929
The service robot was practical		0.709	5.700
The service robot was efficient		0.759	5.540
The service robot could bring convenience to customers	Self-developed	0.686	5.971
The service robot was helpful to customers		0.681	5.871

Autonomy α=0.859; CR=0.899; AVE=0.641			
The service robot could independently complete the operation of the skill	Hu *et al.* (2021)	0.832	5.318
The service robot could independently implement the operation of the skill		0.821	5.404
The service robot could autonomously perform the operation of the skill		0.817	5.393
The service robot could carry out the operation of skills autonomously		0.835	5.416
The service robot could complete its work without direct human intervention	Self-developed	0.691	4.707
Coolness α=0.790; CR=0.864; AVE=0.613			
The service robot was on the cutting edge	Self-developed	0.761	5.864
The service robot was advanced		0.770	5.667
The service robot was cool		0.785	5.436
The service robot was very cool		0.815	5.071
Courtesy α=0.714; CR=0.823; AVE=0.538			
The service robot was polite	Sari *et al.* (2016)	0.760	6.016
The service robot was courteous		0.751	6.002
The service robot treated me with respect	Self-developed	0.722	6.042
The service robot was friendly		0.701	6.082
Cuteness α=0.755; CR=0.845; AVE=0.579			
The service robot was cute	Nenkov and Scott (2014)	0.808	5.822
The service robot was adorable		0.816	5.916
The service robot was endearing		0.781	5.493
The service robot had a lovable appearance	Self-developed	0.623	5.713
Interactivity α=0.860; CR=0.899; AVE=0.641			
The service robot could respond to my questions	Self-developed	0.818	5.569
The service robot had the ability to communicate with me		0.831	5.258
The service robot could understand what I said		0.775	5.167
The service robot could interact with me		0.816	5.564
The service robot could encourage me to interact with it		0.761	4.980
Negative affect α=0.830; CR=0.880; AVE=0.594			
The robot made me feel scared	Self-developed	0.802	1.898
The service robot made me feel fearful		0.799	1.602
I was frightened by the service robot		0.731	1.687
The service robot made me feel disappointed		0.739	1.969
The service robot made me feel uncomfortable		0.781	1.724
Enjoyment α=0.807; CR=0.862; AVE=0.509			
Encountering/Interacting with service robot was enjoyable	Venkatesh (2000)	0.752	5.842
Encountering/Interacting with service robot was pleasant		0.688	5.920
I had fun encountering/interacting with service robot		0.687	5.942
Encountering/Interacting with service robot was interesting	Self-developed	0.715	5.847
Encountering/Interacting with service robot was amusing		0.721	5.824
I felt happy encountering/interacting with service robot		0.719	5.980
Novelty α=0.720; CR=0.826; AVE=0.543			
When I encountered the service robot, I was surprised	Self-developed	0.742	5.636
When I encountered the service robot, I had a feeling of novelty		0.753	5.960
Service robot stimulated my curiosity		0.714	6.071
The experience with service robot was unique	Kim *et al.* (2012)	0.739	5.829
Satisfaction α=0.725; CR=0.829; AVE=0.549			
Overall, how satisfied were you with the service robot?	(Tussyadiah, 2016)	0.717	5.796
When compared with your expectation, how satisfied were you with the service robot?		0.725	5.616
When considering the money you spent, how satisfied were you with the service robot?		0.728	5.371
When considering the time and effort, how satisfied were you with the service robot?		0.791	5.571

Note: Italicised items were developed by this study. Based on the EFA in Phase 1, the item “The service robot was stylish” for coolness has been deleted from the initial item pool; based on the measurement model in Phase 2, the following items have been deleted: "The service robot had a likable voice" for cuteness, "The service robot was thoughtful" for courtesy, "When I encountered the service robot, I experienced something new" and "The experience with service robot satisfied my curiosity" for novelty.