Understanding the drivers of consumers' acceptance and use of service robots in the hotel industry

Abstract

Purpose - This study discovers factors and configurations that influence customers' acceptance behaviors in order to investigate the current hospitality industry utilizing service robots.

Design/methodology/approach - A mix of symmetrical and asymmetrical modeling methods was used for the data analysis. The symmetrical modeling was used to find the net effects, while asymmetrical modeling was adopted to find the combined configurations for hotel guests' robot service acceptance behaviors.

Findings - The results revealed the significant effect of innovativeness, willingness to be a lighthouse customer, personal norms, and concern about service robot performance on acceptance behaviors. In addition, the complex solution models using characteristics of tech-forward consumers, norms and attitude, and uncertainty and concern were found.

Practical implications - The study shows directions to hotel marketers, to help them make customers adopt service robots.

Originality/value – The study explored customer service robot acceptance behaviors based on comprehensive theoretical backgrounds, including the technology acceptance model, theory of planned behavior, norm activation model, and service robot acceptance model.

Keywords: Service robot, tech-forward consumer, hotel industry, innovativeness, technology adoption, personal norm

1. Introduction

While service robots in the hospitality and tourism industry are pervasive, customers' adoption behaviors or attitudes toward robot service remain unfavorably or hesitate (Yu et al., 2023). The rapid advancement of service robots is closely tied to the progress in computer vision, sensors, speech recognition, artificial intelligence (AI), machine learning, and navigational systems, resulting in smarter, more mobile, and cost-effective robots (Collins, 2020). Service robots are described as adaptable and autonomous interfaces that operate within a system, engaging in interactions, communication, and service delivery to cater to customer needs (Wirtz et al., 2018). Therefore, research on consumer behavior towards service robots is necessary because customer behavior is still cautious compared to a rapidly developing industry (Sharma et al., 2023).

Service robots have emerged as key players across various levels and cater to the needs of different stakeholders, including firms, customers, and employees, in the hospitality area (Wirtz et al., 2018). These robots contribute considerably to enhancing operational efficiency, improving customer experiences, and transforming the overall industry landscape. At the micro level, service robots assist in tasks, such as room cleaning, concierge services, and food delivery, streamlining operations within individual establishments (Zhang et al., 2022). At the meso level, service robots enable hotels and hospitality organizations to optimize resource allocation, manage labor utilization, and enhance service quality (Wirtz & Jerger, 2016). At the macro level, the introduction of service robots contributes to the overall competitiveness and innovation of the sector (Wirtz et al., 2018). By leveraging advancements in technology, such as AI and automation, service robots have become integral to the functioning and success of the hospitality industry (Doborjeh et al., 2022). Moreover, the expansion and deployment of service robots in hotels have accelerated since the pandemic (Huang et al., 2024). This is

because these service robots are hygienic and can provide non-contact services that do not involve in-person contact (Liu et al., 2024; Fu et al., 2022).

Although technological progress has been made and the potential advantages of service robots recognized, customers may present unfavorable attitudes or hesitancy towards their adoption, including negative perceptions of robots, worries about privacy and security, and a preference for human engagement. These factors influence how customers perceive and adopt service robots (Liu et al., 2024). Davis (1989) suggests the need to identify the variables that contribute to users' perception of technology, as well as the factors that affect social influence, convenience, and hedonic motivations in technology adoption. Therefore, the role of individual characteristics, including personality traits, such as self-consciousness, personal innovativeness, and other individual differences, in the acceptance and adoption of technology must be investigated (Bhatt, 2022).

A critical analysis of the existing service robot research in the hotel industry reveals several research gaps that necessitate further attention and investigation. First, consumer acceptance and response in the rapidly changing and developing hotel service robot environment in the hotel industry must be explored further (Fu et al., 2022). Second, while most studies focus on the functional value of customer behavior in the service robot context (Jung et al., 2023), a notable dearth of research has investigated consumer characteristics that exert a substantial effect on the behavior of other customers, such as lighthouse customers, opinion leaders, high innovativeness, and personal identity. Last, most consumer behavior studies interpret outcome variables through the simple relationship between variables. This presents theoretical hardships as the failure to find necessary conditions that make it challenging to identify factors that must be included if the desired result is to be achieved (Wattanacharoensil et al., 2024). Therefore, an advanced methodological contribution is required to distinguish the necessary condition toward the outcome variable.

This research aims to examine consumer acceptance and response in the dynamic and evolving environment of hotel service robots. By investigating how individual characteristics influence consumer acceptance, this study seeks to provide further insight into the effective utilization of hotel service robots. Thus, the present research was designed to uncover the determining factors of consumer acceptance behaviors for service robots in the hotel industry. In particular, the current research is to (1) investigate the impact of (a) characteristics of tech-forward consumers, (b) norms and attitude, and (c) uncertainty and concern on consumer acceptance behaviors and (2) uncover the causal recipes, which are the optimum combinations of the variables within (a) characteristics of tech-forward consumers, (b) norms and attitude, and (c) uncertainty and concern, leading to acceptance behaviors for service robots in the hotel sector.

2. Literature review

2.1. Impact of service robots on the hotel industry

Among 34.95 billion US dollars of worldwide robotics market revenue in 2023, 26.09 billion dollars of revenue (75% of the total robotics market) is from service robotics, and it is expected to grow to 32.75 billion dollars in 2027 (Huang et al., 2024). Service robots have been utilized in the hotel industry to assist human labor, reduce labor costs, deliver consistent service, increase efficiency, and provide convenient services to hotel customers (Leung et al., 2023). A service robot can interact and communicate with humans, operates autonomously or semi-autonomously, and is designed to adhere to the behavioral norms expected by individuals (Choi et al., 2020). The hotel's purpose in adopting these robots is to provide assistance and perform tasks to enhance customer experience (Akdim et al., 2023).

The emergence of service robots in hotels is dynamic with new applications and functionalities. One type of service robot is the concierge robot which is designed to provide

information and assistance to guests, such as answering questions, providing directions, and recommending local attractions (Shin & Jeong, 2020). They can enhance the guest experience by offering personalized recommendations and reducing the workload of the human concierge staff. Another type of service robot is the delivery robot, which is equipped with navigation systems and can autonomously navigate through hotel premises to deliver items to guest rooms, such as room service orders or amenities (Kuo et al., 2017). These robots are utilized to perform numerous tasks and services, enhancing the overall guest experience and improving operational efficiency.

The adoption of service robots is motivated by several factors identified in previous research. The factors include the integration of AI and machine learning into robots, the need to replace low-skill jobs for the reduction of labor costs, to enhance productivity and efficiency in the hotel industry, consumers' desire for unique and novel experiences, the health and safety privilege offered by robots, and the desire to improve brand reputation and competitiveness (Leung et al., 2023; Khoa et al., 2023). Customer acceptance behavior has been theorized in consumer behavior literature in order to explain the customer's adoption behavior in various situations (Zhong et al., 2021; Said et al., 2024). While numerous acceptance models have been proposed and evaluated for various applications, a reliable acceptance model and its relevant variables in the context of service robots are still needed (Zhong et al., 2021).

According to the service robot acceptance model (sRAM), consumer reception of service robots is influenced by their ability to meet functional, social-emotional, and relational elements, ultimately achieving role congruency (Writz et al., 2018). Functional elements refer to the robot's ability to perform tasks effectively and fulfill its intended purpose (usefulness, ease to use), social-emotional and relational needs pertain to the robot's ability to establish a sense of warmth and connection with users (humanness, interactivity, social presence), and relational elements explain customer's perception of enjoyable and credible interaction (trust

and rapport) (Wirtz et al., 2018; Lu et al., 2020). Thus, a research framework has been developed based on these theoretical backgrounds of service robot acceptance.

2.2. Characteristics of tech-forward consumers

2.2.1. Innovativeness

Customer innovativeness is identified as an individual's inclination and willingness to adapt to new products or services at an earlier stage, rather than sticking to their current or previous choices (Jung et al., 2023). Innovative customers are characterized by their openness to trying new things and their enthusiasm for diverse experiences, exhibiting a positive attitude toward novelty (Radic et al., 2022). Research has brought attention to the importance of innovativeness as a personal trait that influences consumer behavior toward new technology products and services. By embracing innovation, customers contribute to the advancement and adoption of new offerings in the market (Kim et al., 2021).

In the technology approach and adoption literature, customer innovativeness has been utilized to investigate the influence of new technology adoption in various settings (Boo & Chua, 2022). Consumers who possess a higher degree of innovativeness are more likely to embrace and appreciate the adoption of new technologies, recognizing it as a valuable action (Park & Jun, 2003). Therefore, this study advocates that customers who exhibit high levels of innovativeness tend to experience satisfaction and pleasure when adopting new innovative technologies, perceiving this behavior as valuable. The study aims to examine the significant impact of customer innovativeness on acceptance behaviors toward service robots. To accomplish this goal, the study establishes a hypothesis to test the relationship between customer innovativeness and acceptance behaviors for service robots.

Hypothesis 1-1: Customer innovativeness significantly increases acceptance behaviors.

2.2.2. Willingness to be a lighthouse customer

Finger and Samwer (2013) introduced the lighthouse customer who early adopted a service or product and became a customer of reference. Lighthouse customers tend to try new services or products in the early introductory stage. It is different from innovativeness in that innovativeness focuses on creativity, a personal trait, whereas willingness to be a lighthouse customer is about understanding and acquiring new products and influencing peers in the adoption process (Chou & Lin, 2023). Strebinger and Treiblmaier (2022) profiled lighthouse customers in hotel booking applications and suggested the characteristics of lighthouse customers: (1) young, who tend to embrace new technology readily; (2) high level of education, and (3) high technology acceptance. Lighthouse customers, who are psychologically distinct from their peers and often hold influential positions, play a pivotal role in the early adoption of innovations (Jung et al., 2023). Lighthouse customers, also known as early adopters, are individuals who are eager to embrace and utilize new technologies before they become mainstream.

Previous literature suggests that lighthouse customers are more likely to have more positive acceptance behavior (Hardman et al., 2017). By understanding and addressing the willingness to be a lighthouse customer, hotels can effectively promote the inclusion of new technologies and stay ahead in the competitive market. Thus, this study argues that willingness to be a lighthouse customer is one of the significant customer characteristics of tech-forward consumers and establishes a hypothesis to test the relationship between willingness to be a lighthouse customer and acceptance behaviors for service robots.

Hypothesis 1-2: Willingness to become a lighthouse customer significantly increases acceptance behaviors.

2.2.3. Self-identity

Self-identity indicates an individual's perception and understanding of themselves, encompassing their beliefs, values, roles, and characteristics that define who they are (Ashforth & Mael, 1989). Understanding the influence of self-identity on behavior is significant to various domains, including psychology, marketing, and organizational behavior, because it provides insights into individuals' motivations and decision-making processes. Self-identity plays a crucial role in motivating behavior because individuals are inherently identity-conscious beings who are inclined to engage in behaviors that align with and reflect their self-identity (Stets & Burke, 2003). When individuals perceive a strong connection between their behavior and their self-identity, they tend to be involved in behaviors that are congruent with their self-identity (Manosuthi et al., 2020). This alignment between behavior and self-identity enhances individuals' sense of authenticity and fulfillment. Self-identity has been utilized in how individuals perceive themselves in relation to new technologies and how they form opinions and behave toward them (Jung et al., 2023). Leung et al. (2018) tested automation features with advanced technology in various contexts and discovered that an individual's acceptance behaviors vary depending on the level of identity-drivenness. Therefore, this study considers self-identity as a significant concept to explain the acceptance behavior of service robots and establishes the following hypothesis:

Hypothesis 1-3: Self-identity significantly increases acceptance behaviors.

2.3. Norms and attitude

2.3.1. Personal norms

The norm activation model (NAM) is a theoretical framework that explains the relationship between personal norms and behavior intention (Schwartz, 1977). According to NAM, a personal norm is known as an individual's moral obligation or responsibility to accomplish or refrain from certain actions. Within the norm activation process, the personal norm is considered an essential construct and the most proximal variable of behavioral intention. Personal norm strongly influences their intention and behavior when it comes to embracing new technologies (Ho et al., 2017). By considering personal norms within the context of behavior intention, the NAM provides a valuable framework for understanding the motivational variables that drive an individual's behaviors. This model proposes that an individual's acts and behavior are based on personal norms or moral obligation, and this was found to be a strong predictor of technology acceptance behaviors (Toft et al., 2014). Therefore, in accordance with the NAM model this study proposes that consumers accept technology because they feel a moral obligation in a pro-social way. Personal norms or moral obligations have been utilized to investigate customer intention and behavior toward robot service (Jung et al., 2023). Personal norms also have been used to elucidate individual behaviors in various technology acceptance contexts, such as information systems (Bhattacherjee, 2001), electronic vehicles (Zhang et al., 2022), cloud storage (Ho et al., 2017), and food delivery service (Kim & Hwang, 2020). Therefore, the current study supposed that customers' acceptance behaviors toward service robots are influenced by personal norms, which explains how much individuals personally internalized new technology and service robots. Previous literature consistently supports the notion that personal norms have a significant influence on an individual's technology-related acceptance behavior. Therefore, this study established the following hypothesis:

Hypothesis 2-1: Hotel customer's personal norms toward service robot technologies significantly increase acceptance behaviors on service robots.

2.3.2. Attitude

Customer attitude refers to the opinions, beliefs, and evaluations that customers hold toward hospitality services, establishments, and experiences. It plays a key role in shaping customer behavior, satisfaction, loyalty, and intention to revisit or recommend a hospitality establishment (Yu et al., 2024). Positive attitudes toward a product or service have been found to be associated with favorable customer behavior, including positive word-of-mouth, repurchasing, and brand loyalty (Lee & Back, 2009). Conversely, negative attitudes can result in customer dissatisfaction, decreased purchase intentions, and even customer defection (Vogel et al., 2008). Moreover, positive attitudes toward technology have been found to be associated with favorable customer behavior, such as increased usage intentions and higher adoption rates (Gonzalez-Jimenez & Costa Pinto, 2024). When customers hold positive feelings toward technology, they are more likely to express interest in using it and show a willingness to adopt it. These positive attitudes can serve as a provocation behind customers' intentions to engage with and embrace technological innovations. Especially in the research on technology adoption behavior and intention in the hospitality segment, numerous studies have confirmed that customer attitudes positively and significantly influence adoption behaviors (Boo & Chua, 2022; Yu et al., 2024). This study defines attitude as an individual's predisposition toward service robots regarding favorability (Lin & Mattila, 2021). Therefore, the study proposes the following hypothesis to examine the relationship between attitude toward service robots and acceptance behavior:

Hypothesis 2-2: Hotel customer's attitude toward service robot technologies significantly increase acceptance behaviors on service robots

2.4. Uncertainty and concern

2.4.1. Uncertainty about high-tech services

Customer uncertainty refers to the lack of comfort and security that customers may have regarding the use, benefits, or outcomes of products or services (Chua et al., 2021). This uncertainty can arise from various factors, such as the complexity and evolution of technology, inadequate information available to decision-makers, and environmental uncertainties (Buhalis & Law, 2008). According to the diffusion of innovation (Rogers, 2010), the adoption of innovation is perceived as a process aimed at reducing uncertainty and gathering information. Hospitality services and products should be designed to address customer uncertainty effectively to achieve successful management (Tuerlan et al., 2021). Previous research found that the level of uncertainty has a significant relationship with technology adoption and approach (or avoidance) behavior (Chua et al., 2021). Therefore, the current study supposed that uncertainty levels about high-tech services significantly influence customer's acceptance behavior toward service robots. Thus, hypothesis 3-1 is proposed to examine the relationship between customer's uncertainty level and acceptance behavior toward service robots.

Hypothesis 3-1: Hotel customer's uncertainty about high-tech services significantly decreases acceptance behaviors on service robots

2.4.2. Concern about service robot performance

Customers express various concerns related to trust, confidence, operational matters, physical aspects, and social activities (Chua et al., 2023). These concerns can arise from various

technology-related factors, such as privacy and security issues in mobile commerce (Wu & Wang, 2005), the authenticity and dependability of technology in self-service (Lee & Yi, 2022), and the potential negative effects on individuals or society in AI service (Ostrom et al., 2019). Concerns about technology can influence individuals' intentions and behaviors toward its adoption or use (Ariza-Montes et al., 2023; Bhattacherjee, 2001). In the current study, concern designates the importance of efficiency, change, and process via service robots (Barbarossa et al., 2015). A previous study has shown that customer concern plays an important role in influencing consumer usage intention and acceptance behavior (Khanra et al., 2021). By recognizing and addressing customer concerns, the hospitality industry can better meet customer needs, improve customer experiences, and foster long-term relationships with its target audience. Therefore, this study considered that customer's concerns significantly influence acceptance behavior toward service robots and established the following hypothesis:

Hypothesis 3-2: Hotel customer's concern about service robot performance significantly increases acceptance behaviors on service robots

3. Research methods

3.1. Composition of measurement items and data collection procedure

This study comprised eight constructs, including three characteristics of tech-forward consumers (innovativeness, willingness to be a lighthouse customer, self-identity), two norms and attitude (personal norms, attitude), two uncertainty and concerns (uncertainty about high-tech services, concerns about service robot performance), and an outcome variable (acceptance behaviors for service robots). The measurement items of each element were adopted from previous studies, which are as follows: Three items for innovativeness were extracted from Wang and Lin (2021). Four items for willingness to be a lighthouse customer were developed

based on Parasuraman and Colby (2015). Three measurement items for self-identity were taken from Barbarossa et al. (2015). Personal norm consisted of four items, two from Cauberghe et al. (2021), one from Wu et al. (2021), and one from Xu et al. (2020). Two scales for attitude were obtained from Lin and Mattila (2021). Uncertainty about high-tech services was gauged with six items taken from Parasuraman and Colby (2015). Three "concern about service robot performance" measures were from Barbarossa et al. (2015). Last, five measurement scales for acceptance behaviors for service robots were developed on the basis of Lin and Matilla (2021) and Barbarossa et al. (2015). Each measurement item was balanced using a seven-point Likert scale (1 – "extremely disagree/extremely negative"; 7 – "extremely agree/extremely positive"), and the items were not duplicated.

The survey was conducted through two biggest online survey companies in Korea, namely, Embrain for Korean and Entrust for Chinese, because the survey was conducted in two countries. The study was specially conducted in Korea and China because they are known to be pioneers of service robots (Cheng et al., 2019). The survey was first made in English and then translated into Korean and Chinese by two bilingual translators. To select suitable participants for the study, the survey included two screening questions; (1) How old is your age? (2) Have you stayed at a luxury hotel within the last 2 years?, and was conducted on adults who stayed at a hotel. 2 years was particularly selected as a screening question because 2019 was the year that Korea and China hotels started adopting service robots (Byun, 2019). As a consequence, a total of 365 valid data were collected from September 2, 2021 to September 9, 2021. The survey consisted of three parts: introduction, measurement items, and demographic information. As proposed in the introduction section, the aim of the study and the results to be expected were explained to the participants. Then, questions related to each variable were asked, followed by demographic questions.

3.2. Research methods

The current research was processed following these steps. First, data were collected after the survey was finalized. Second, data quality was checked via confirmatory factor analysis (CFA). Third, the net effect was obtained using AMOS 22.0. Fourth, necessary condition analysis was conducted to determine whether the relevant element exists. Fifth, asymmetrical modeling was performed using fuzzy-set qualitative comparative analysis (fsQCA). The fsQCA is used in the research when identifying complex combinations that influence outcome conditions (De Canio et al., 2020). It is adopted in social sciences looking for complex conditions and also applied to the research related to consumer intentions in the hospitality and tourism industry (e.g. Foroughi et al., 2024; Satar et al., 2024). In addition, the fsQCA especially searches the necessary and dominant conditions that are needed for outcome variables (Thiem, 2021). Thus, the method was adopted to achieve the goals of the study.

3.3. Participants profile

To check the characteristics of respondents, gender, nationality, marital status, age, education level, and income were asked in the demographic information part. Among 365 participants, 52.9% (n = 193) were male, and 47.1% (n = 172) were female. Given that the study was conducted in two countries, 46.6% (n = 170) were Chinese, and 53.4% (n = 195) were Korean. Furthermore, marital status, age, level of education, and annual household income were asked. Moreover, an additional question of whether the survey respondents have ever experienced service robots at a hotel was asked to find out the use of service robots. Most of the participants (75.1%, n = 274) answered “no,” whereas 24.9% (n = 91) selected “yes.”

4. Results

4.1. Results of CFA

All factor loadings for variables ranged from 0.643 to 0.900, which was over the minimum value of 0.6 (Chin, 1998). Composite reliability (CR) values ranged from 0.809 to 0.930, and the average variance extracted (AVE) ranged from 0.516 to 0.754. All the CR and AVE values exceeded the recommended levels of 0.7 and 0.5 (Hair et al., 2017). In addition, each variable's AVE values were lower than its corresponding CR values (Fornell & Larcker, 1981). The correlation values ranged from 0.176 to 0.817. The squared AVE values ranged from 0.718 to 0.868, mostly exceeding the corresponding correlation values. By confirming these values, internal consistency, discriminate validity, and convergent validity were checked. Furthermore, the goodness-of-fit statistics for the baseline model showed satisfactory level ($\chi 2$ = 578.561, df = 332, $\chi 2/df$ = 1.743, $p < 0.01$, IFI = 0.969, TLI = 0.959, CFI = 0.969, NFI = 0.930, RFI = 0.908, RMSEA = 0.045).

4.2. Results of net effect and necessary condition analysis

The net effect of each of the seven variables was investigated. Four variables, innovativeness ($\beta = 0.107$, $p < 0.001$), willingness to be a lighthouse customer ($\beta = 0.192$, $p < 0.001$), personal norms ($\beta = 0.281$, $p < 0.001$), and concern about service robot performance ($\beta = 0.626$, $p < 0.001$) had a significant and meaningful effect on acceptance behaviors for service robots. In addition, self-identity ($\beta = 0.016$, $p > 0.05$), attitude ($\beta = -0.050$, $p > 0.05$), and uncertainty about high-tech services ($\beta = 0.034$, $p > 0.05$) were not supported. The results are presented in **Figure 1**.

A necessary condition is usually considered to be established when the consistency exceeds 0.9 (Olya et al., 2018). To confirm whether the necessary conditions exist, necessary condition analysis through fsQCA was performed. All of the antecedent conditions were tested, and consistencies ranged between 0.669 and 0.875. Thus, no necessary condition existed for

acceptance behaviors for service robots. The necessary condition results are organized in **Table 1**.

(Insert Figure 1)

(Insert Table 1)

4.3. Results of asymmetrical modeling

Results of asymmetrical modeling identified configurations for high (the most influential combinations) and low (the least influential combinations) levels of acceptance behaviors for service robots. A total of four cases for each high and low level were demonstrated for configurations, including characteristics of tech-forward consumers, norms and attitude, uncertainty and concern, and all ingredients. The three models were shown for the high level of acceptance behaviors with tech-forward consumers (coverage: 0.923, consistency: 0.733), which were high innovativeness (AB. M1: IN), high willingness to be a lighthouse customer (AB. M2: WA), and high self-identity (AB. M3: SI). One causal model each was predicted using norms and attitude and uncertainty and concern conditions. With norms and attitude (coverage: 0.847, consistency: 0.852), a high attitude (AB. M1: AT) was needed, whereas with uncertainty and concern (coverage: 0.844, consistency: 0.819), a high concern about service robot performance (AB. M1: CP) was required for high acceptance behaviors for service robots. Then, five causal models were indicated when applying all ingredients (coverage: 0.761, consistency: 0.899). These models were as follows: low innovativeness, willingness to be a lighthouse customer, self-identity, concern about service robot performance, uncertainty about high-tech services, and high attitude (AB. M1: ~IN*~WA*~SI*~CP*AT*~US); high innovativeness, willingness to be a lighthouse customer, self-identity, concern about service robot performance, personal norms, and low uncertainty

about high-tech services (AB. M2: IN*WA*SI*CP*PN*~US); and high innovativeness, willingness to be a lighthouse customer, concern about service robot performance, personal norms, attitude, and low uncertainty about high-tech services (AB. M3: IN*WA*CP*PN*AT*~US).

The configurations for the low level of acceptance behaviors for service robots using characteristics of tech-forward consumers' variables (coverage: 0.939, 0.818) were low self-identity (~AB. M1: ~SI), low willingness to be a lighthouse customer (~AB. M2: ~WA), and low innovativeness (~AB. M3: ~IN). Two recipes were identified with norms and attitude factors (coverage: 0.941, consistency: 0.850), which were low attitude (~AB. M1: ~AT) and low personal norms (~AB. M2: ~PN). A configuration made with uncertainty and concern factors (coverage: 0.859, consistency: 0.879) was low concern about service robot performance (~AB. M1: ~CP). Six causal recipes with all ingredients that lead to low levels of acceptance behaviors for service robots (coverage: 0.758, consistency: 0.944) were defined: low self-identity, concern about service robot performance, willingness to be a lighthouse customer, uncertainty about high-tech services, innovativeness, and high attitude (~AB. M1: ~SI*~CP*AT*~WA*~US*~IN); low self-identity, personal norms, attitude, willingness to be a lighthouse customer, innovativeness, and high uncertainty about high-tech services (~AB. M2: ~SI*~PN*~AT*~WA*US*~IN); and low self-identity, concern about service robot performance, personal norms, attitude, innovativeness, and high uncertainty about high-tech services (~AB. M3: ~SI*~CP*~PN*~AT*US*~IN).

All models were subject to a coverage cut-off of 0.5 and a consistency cut-off of 0.8 (Wang et al. 2023). Consistency shows how strong the model is related to the outcome, while coverage refers to how much of the variation in the results is explained by casual conditions (Veri et al., 2018). However, the models with characteristics of tech-forward consumers for

high acceptance behaviors did not exceed the consistency cut-off. Therefore, H1-3 were supported. The full results are presented in **Table 2**.

(Insert Table 2)

5. Discussion and implications

This research attached sRAM with the technology acceptance model (TAM), theory of planned behavior (TPB), and norm activation model (NAM) to discover the robot service acceptance behavior of luxury hotel guests. The study revealed that innovativeness, willingness to be a lighthouse customer, personal norms, and concern about service robot performance have a significant net impact on acceptance behaviors for service robots. The finding is in line with previous technology studies (Hardman et al., 2017; Ho et al., 2017; Khanra et al., 2021). However, in contrast to previous studies (Boo & Chua, 2022; Chua et al., 2021), self-identity, attitude, and uncertainty about high-tech services did not show a net effect.

Interestingly, the fsQCA results revealed that all three areas, which are functional, social-emotional, and relational, should be considered together when looking at luxury hotel consumers' acceptance behaviors. Even the models using only TAM, TPB, or NAM elements showed that the single factor's impact is important, the most effective models using all variables were found to be a mixture of all three models and theory, which is in line with sRAM's theoretical findings. The most effective model using all variables was a combination of innovativeness, willingness to be a lighthouse customer, self-identity, concern about service robot performance, personal norms, and negation of uncertainty about high-tech services, followed by a combination of innovativeness, willingness to be a lighthouse customer, concern about service robot performance, personal norms, attitude, and negation of uncertainty about

high-tech services. No necessary conditions were found for the behavior, therefore, the combinations of TAM, TPB, and NAM elements were crucial.

5.1. Theoretical implications

The study provides noteworthy outcomes to the hospitality industry and robot technology scholars. Customers' adoption behavior does not happen from one element, and people's behavior is determined by multiple factors. First, this study contributes to the study of complex consumer psychology and robot research by presenting a complex model using fsQCA that influences service robot acceptance behavior. Previous studies have focused on the individual effects, not considering the complexity of the customer's intention. Thus, this study has focused on the complex impacts of individual variables, broadening consumer-technology-related studies. In contrast to existing research (Boo & Chua, 2022; Hardman et al., 2017; Chua et al., 2021; Khanra et al., 2021), self-identity, attitude, and uncertainty about high-tech services are found to have no individual effect on acceptance behaviors for service robots at a hotel. However, the fsQCA result shows that even without individual effects, each factor plays a significant role in combinations. For example, the 4th model for the high level was a combination of willingness to become an early adopter, self-identity, concern about service robot performance, personal norms, attitude, and uncertainty, which includes all factors that were found to have no individual impact.

The paper provides evidence of the importance of studying complex solutions in consumer behavior studies. When the functional, social-emotional, and relational elements are studied separately, the results show individual elements affecting the behaviors. However, when considering all elements that could be affected in characteristics, norms and attitude, and uncertainty and concern, the combination of variables is found to be the only valuable models

and have the greatest impact. This serves as proof that in social research, where there are many influencing factors for the same result, various perspectives should be combined for research.

Second, this study shows that acceptance behavior cannot be highly achieved if one of the functional, social-emotional, or relational values is missing. The findings support Wirtz et al. (2018)'s service robot acceptance model (sRAM), and by matching each sRAM function with the TAM, TPB, and NAM, the study gives a discovery of sRAM. Further, the high acceptance models are combined with elements in all three categories, even without necessary conditions. Especially, this paper shows that combining characteristics of tech-forward consumers, norms and attitudes, uncertainty and concern has a crucial impact on the technology acceptance level. Therefore, it has proven how the combination of models and theories is crucial to consumers' technology acceptance in the hotel area.

Third, this study adds depth to hospitality technology research by providing not only acceptance behavior but also mixed solutions that hinder reaching the acceptance behaviors for service robots. For example, the results of the negation condition reveal that low willingness to be a lighthouse customer, low attitude, and low concern about service robot performance significantly impact on the negation of acceptance behaviors for the robots. In the low condition, it is shown that the negation conditions of the study variables have a huge negative impact on the acceptance level. Thus, these results further emphasize the importance of studying the characteristics of tech-forward consumers, norms and attitude, and uncertainty and concern variables.

5.2. Managerial implications

This study provides managers the guidelines for the functional, relational, and social-emotional elements. Especially, the result shows how to effectively integrate customer expectations into adoptions. The sRAM has introduced that hotels should provide robots with

all three categories (functional, relational, and social-emotional) to make travelers accept and use hotel robots. This study especially combines the TPB, NAM, and TAM with sRAM's each category informing hotel managers on what specific factors they should focus on. Although it is generally known that it is easy for service robots to enter mid-level hotels (Tung & Tse, 2023), the findings could be used to increase the acceptance amount of robot service uses among luxury hotel guests.

For example, hotel operators should consider innovativeness, willingness to be a lighthouse customer, concern about service robot performance, and personal norms for the strategy to be most effective. In addition, uncertainty about high-tech services should be calculated because it negatively affects consumers. Thus, hotel operators introducing robot services should develop a marketing strategy for consumers to be familiar with service robots by lowering consumers' anxiety about robots and increasing their awareness of the technology to influence overall behavior. However, when considering these elements in marketing, hotel marketers should recognize that applying them in the wrong direction will actually play a negative role. If self-identity, willingness to be a lighthouse customer, innovativeness, attitude, personal norms, or concern about service robot performance operates under a negation condition, customers' acceptance behavior decreases. Accordingly, the definitions and explanations for each element of the study must be actively utilized to ensure correct application.

Looking at the most impactful combination from the results, it has been discovered that the uncertainty should be lowered among early adopters and innovativness customers, who are interested in technologies. The majority of customers follow lighthouse customers (Kirjavainen et al., 2022), therefore, improving the perception of lighthouse customers is a priority. Thus, hotel marketers should test among lighthouse hotel customers in advance. For instance, if the marketers invite the technology area social media influencers and introduce a

new service robot of the hotel, they should get familiar with the robots and share them with their followers. Then, the users who have accessed their content would easily get closer to the hotel's new service robots. Thus, marketers should demonstrate or invite lighthouse customers to show them first, explaining the advantages of the service robots and lowering their concerns about uncertainty. The markers could expect word-of-mouth benefits through demonstrations from lighthouse customers to spread the word to other consumers after using it in advance. Then, it would be easier for luxury hotel customers to accept the newly adopted service robots.

Additionally, managers should pay increased attention to concerns about service robot performance even if it is not a necessary condition for the acceptance behaviors of consumers for service robots. By adopting robot services, hotels are replacing human work, and consumers want to be sure that robots are more efficient and convenient than human agents and meet their expectations. The results of this study indicate that hotels should find robots that can actually meet customer needs and place them in the right places in the hotel, rather than robots that are simply designed to reduce prices. In conclusion, as more hotels currently introduce robot systems, this research will be a good guide for hotel marketers.

5.3. Limitations and future research

This study has some limitations that can be studied in the future. First, research data were only collected in China and Korea. Thus, the result of this study might not apply to other countries. Second, the study participants included those who have stayed at a hotel within the last 2 years and, therefore, have knowledge about the hotel systems. However, 75.1% of the respondents answered that they have not experienced service robots at a hotel. This could be the result of the data collected in 2021. Third, the study was based on the customer's intention about robot services. However, if the focus was on service employees, the result would be

different. Fourth, the adoption intention was used as a dependent variable. Using actual behavior as an outcome variable could give more insights to hotel operators.

To strengthen these weaknesses, the concept of the study could be adopted for other countries and could increase external validity. If future studies are conducted in other countries, cross-cultural research could be performed. Also, hotels adopting robot services are increasing. Therefore, more consumers should have experienced the actual robot service. Thus, future studies could limit the sample to participants who have experienced service robots and compare the results with this study. Furthermore, the researchers can focus on actual behaviors instead of intention. If there were different prerequisite conditions for the same outcome in previous studies, it would be good for researchers to study combination of conditions for the outcome, also find the necessary conditions for the consumer actions. In addition, technology-related variables can be added that influence people's technology use and check the relation to acceptance behaviors. Morever, future studies should focus on the adoption intention of service employees side, and broaden the scope of the study.

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Table 1. Results of necessary condition analysis

Antecedent condition	Outcome condition	
	Approach behaviors for service robots (AB)	
	Consistency	Coverage
IN	0.835	0.805
~IN	0.685	0.535
WA	0.819	0.811
~WA	0.687	0.526
SI	0.837	0.807
~SI	0.686	0.535
PN	0.875	0.812
~PN	0.664	0.536
AT	0.847	0.852
~AT	0.669	0.505
US	0.673	0.556
~US	0.790	0.713
CP	0.844	0.819
~CP	0.679	0.528

Note 1. ~ indicates negation condition

Note 2. IN: innovativeness, WA: willingness to be an early adopter, SI: self-identity, PN: personal norms, AT: attitude, US: uncertainty about high-tech services, CP: concern about service robot performance, AB: approach behaviors for service robots

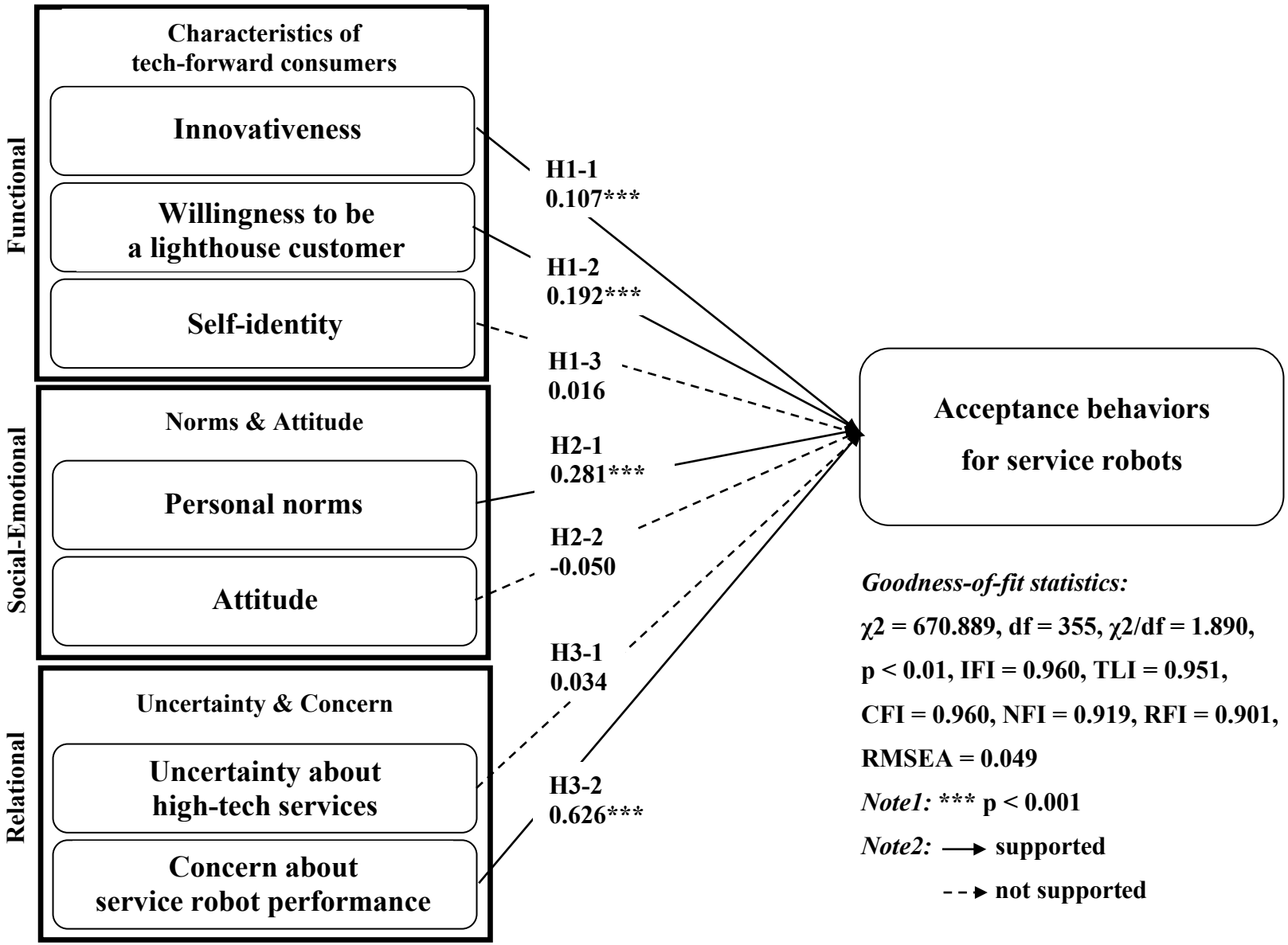
Table 2. Results of asymmetrical modeling

Configurations	Raw coverage	Unique coverage	Consistency
Configurations for high level of AB			
AB = *f* (IN, WA, SI)			
IN	0.835	0.029	0.805
WA	0.819	0.020	0.811
SI	0.837	0.032	0.807
Solution coverage: 0.923			
Solution consistency: 0.733			
AB = *f* (PN, AT)			
AT	0.847	0.847	0.852
Solution coverage: 0.847			
Solution consistency: 0.852			
AB = *f* (US, CP)			
CP	0.844	0.844	0.819
Solution coverage: 0.844			
Solution consistency: 0.819			
AB= *f* (IN, WA, SI, PN, AT, US, CP)			
~IN*~WA*~SI*~CP*AT*~US	0.433	0.068	0.925
IN*WA*SI*CP*PN*~US	0.590	0.112	0.973
IN*WA*CP*PN*AT*~US	0.580	0.008	0.982
WA*SI*CP*PN*AT*US	0.511	0.053	0.964
IN*WA*SI*~CP*~PN*~AT*US	0.390	0.016	0.924
Solution coverage: 0.761			
Solution consistency: 0.899			
Configurations for low level of AB			
~AB = *f* (IN, WA, SI)			
~SI	0.849	0.031	0.873
~WA	0.855	0.024	0.861
~IN	0.846	0.017	0.871
Solution coverage: 0.939			
Solution consistency: 0.818			
~AB = *f* (PN, AT)			
~AT	0.888	0.095	0.884
~PN	0.846	0.053	0.899
Solution coverage: 0.941			
Solution consistency: 0.850			
~AB = *f* (US, CP)			
~CP	0.859	0.859	0.879
Solution coverage: 0.859			
Solution consistency: 0.879			
~AB = *f* (IN, WA, SI, PN, AT, US, CP)			
~SI*~CP*AT*~WA*~US*~IN	0.338	0.005	0.952
~SI*~PN*~AT*~WA*US*~IN	0.554	0.013	0.982
~SI*~CP*~PN*~AT*US*~IN	0.554	0.014	0.980
~SI*CP*PN*~AT*WA*~US*IN	0.329	0.047	0.959
~SI*~CP*~PN*~WA*~US*~IN	0.433	0.002	0.960
~SI*~CP*~PN*~AT*~WA*~IN	0.645	0.009	0.976
Solution coverage: 0.758			
Solution consistency: 0.944			

Note 1. ~ indicates negation condition

Note 2. IN: innovativeness, WA: willingness to be an early adopter, SI: self-identity, PN: personal norms, AT: attitude, US: uncertainty about high-tech services, CP: concern about service robot performance, AB: approach behaviors for service robots

Figure 1. Theoretical framework and sufficient antecedents (net effect)



Supplementary material 1. Characteristics of the Sample

Characteristics		Number	Percentage (%)
Gender	Male	193	52.9
	Female	172	47.1
Nationality	Chinese	170	46.6
	Korean	195	53.4
Marital status	Married	165	45.2
	Not married	198	54.2
	Others	2	0.5
Age	20–29	100	27.4
	30–39	98	26.8
	40–49	79	21.6
	50–59	46	12.6
	60 or more	42	11.5
Highest level of education	High school degree	22	6.0
	Two-year degree/community college degree	53	14.5
	Bachelor's degree	236	64.7
	Master's degree	44	12.1
	Ph.D.	10	2.7
Annual household income (US dollars)	$19,999 or under	11	3.0
	$20,000–$39,999	87	23.8
	$40,000–$59,999	107	29.3
	$60,000–$79,999	78	21.4
	$80,000–$99,999	47	12.9
	$100,000 or more	35	9.6
Experienced service robots at a hotel	Yes	91	24.9
	No	274	75.1
		365	**100**

Supplementary material 2. Results of confirmatory factor analysis

		β	AVE	CR
IN1	If I hear about a new robot technology, I look for a way to gain experience with it.	0.736	0.630	0.836
IN2	Among my peers, I am usually the first to try out a new technology.	0.799		
IN3	I like to experiment with new robot technologies.	0.843		
WA1	Other people come to me for advice on new technologies.	0.876	0.692	0.900
WA2	In general, I am among the first in my circle of friends to acquire new technology when it appears.	0.824		
WA3	I can usually figure out new high-tech products and services without help from others.	0.765		
WA4	I keep up with the latest technological developments in my areas of interest.	0.859		
SI1	I think of myself as someone who is concerned about robot product issues.	0.820	0.677	0.863
SI2	I think of myself as a "robot" consumer.	0.833		
SI3	I would describe myself as a technologically conscious consumer.	0.815		
PN1	I have the moral obligation to technology.	0.643	0.516	0.809
PN2	Not accepting robots is against my personal norms.	0.649		
PN3	My decision to adopt robot technology is fully in line with my moral conviction.	0.772		
PN4	Because of my own values, I feel an obligation to behave in a technology-friendly way.	0.796		
AT1	My personal attitude toward service robots in general is: extremely negative = 1 to extremely positive = 7.	0.900	0.754	0.859
AT2	My personal attitude toward engaging or interacting with service robots is: extremely negative = 1 to extremely positive = 7.	0.835		
US1	When I receive technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do.	0.805	0.690	0.930
US2	Technical support lines are not helpful because they do not explain things in terms I understand.	0.864		
US3	Sometimes I think that technology systems are not designed for use by ordinary people.	0.799		
US4	There is no such thing as a manual for a high-tech product or service that's written in plain language.	0.873		
US5	People are too dependent on technology to do things for them.	0.799		
US6	Too much technology distracts people to a point that is harmful.	0.840		
CP1	It is important to me whether service robot is more efficient than human.	0.788	0.611	0.825
CP2	It is important to me if it meets my expectation about social technological changes.	0.758		
CP3	It is important to me whether delivering process gets simplified by service robots than by human employees.	0.799		
AB1	Next time I visit a hotel, I will consider staying at a hotel with robot services.	0.810	0.626	0.893
AB2	I welcome the adoption of service robots in hotels.	0.848		
AB3	I predict that I will frequently use robot services at a hotel in the near future.	0.741		
AB4	I would accept service robots serving me at a hotel because it will be the norm in the future.	0.756		

AB5	I am willing to adapt to using service robots in hotels, as they will greatly reduce human contact.	0.795

Note1. Goodness-of-fit statistics for the baseline model: $\chi 2 = 578.561$, df = 332, $\chi 2/df = 1.743$, $p < 0.01$, IFI = 0.969, TLI = 0.959, CFI = 0.969, NFI = 0.930, RFI = 0.908, RMSEA = 0.045

Note2. IN: innovativeness, WA: willingness to be an early adopter, SI: self-identity, PN: personal norms, AT: attitude, US: uncertainty about high-tech services, CP: concern about service robot performance, AB: approach behaviors for service robots