Technology acceptance before and after COVID-19: No-touch service from hotel robots

Abstract

Purpose: This study investigated the consumer acceptance of robots in hotels before and after COVID-19, with a specific emphasis on whether COVID-19 had a significant effect on the acceptance of robots by hotel guests, and whether guests had higher levels of acceptance of hotel robots since the initial COVID-19 outbreak was brought under control in China.

Design/methodology/approach: The sample for this research included Chinese hotel guests before and after COVID-19, with 247 responses obtained before its outbreak and a further 601 responses gathered after. Several hypotheses were developed and tested in a pseudo-experimental design.

Findings: The results showed that COVID-19 increased hotel guest acceptance of robots. After COVID-19, the perceived importance of the usefulness, social influence, attitude and value of robots increased, while the perceived importance of the ease of use and anthropomorphism of robots decreased. As a contactless service, the usefulness of robots was more valued by customers. This led customers to lower their requirements for the ease of use of robots. In addition, people were more concerned about the social influences on robot use.

Research limitations/implications: Hotel guest attitudes and behavioral intentions towards robots and the services they can provide are changing. However, whether this change is purely ephemeral and motivated by a pragmatic stance triggered by

COVID-19 remains to be established.

Practical implications: The hospitality industry is encouraged to create a new profile of guests in terms of their favorable or unfavorable disposition towards being served by robots. Hotels should consider the deployment of robots according to the demographic characteristics of customers (e.g., according to guest age levels).

Uniqueness/originality: This research demonstrated that major crises affect customer attitudes and behaviors toward new technologies. COVID-19 resulted in guests paying more attention to the advantages of services offered by hotel robots as a means of reducing the probability of contagion.

Keywords: COVID-19; robots; hotels; Technology Acceptance Model (TAM); artificial intelligence (AI)

Introduction

The international hospitality industry has faced, and will continue to face, a technology-based revolution (Law & Jogaratnam, 2005; Leung, 2019; Zhang, Gordon, Buhalis, & Ding, 2018; Assiouras, Skourtis, Giannopoulos, Buhalis & Koniordos, 2019; Buhalis, Harwood, Bogicevic, Viglia, Beldona, & Hofacker, 2019; Buhalis, 2020). To improve operational efficiency, managers in hospitality and tourism are starting to consider the possibility of introducing service robots in their establishments (Belanche, Casaló, & Flavián, 2020). Hotel robots deliver entertainment, as well as physical assistance, including transport, baggage check-in, guidance, and general information. In many cases, hotel robots have helped to provide enhancements to customer service whilst reducing operational costs, and increasing efficiency and productivity (Xu, Stienmetz, & Ashton, 2020).

The COVID-19 pandemic, which started in Wuhan (China) in January 2020, has had a devastating and widespread impact on travel, tourism and hospitality globally (Ivanov, Webster, Stoilova, & Slobodskoy, 2020; Pillai, Haldorai, Seo, & Kim, 2021). China's economic development was severely impacted by the pandemic, especially in the hospitality industry (Hao, Xiao, & Chon, 2020). Major changes in consumer behavior triggered by China’s national lockdown initiative to contain the spread of the virus led to a sudden and drastic drop in hotel room bookings, which the industry is still recovering from today (Jiang & Wen, 2020). In the meantime, and whilst the lockdown was in place, hotels were left with on-going operating costs related to manpower and energy consumption. In addition，the threat of COVID-19 triggered employee absences (Karatepe, Saydam, & Okumus, 2021), leading to significant losses for hotels. To reduce these losses, hospitality companies had to innovate and explore "self-help" strategies. The needs of residential customers for contact-less health and safety solutions that respected lockdown guidelines and social distancing rules were actively used for this purpose and for new business development.

As China emerged from nationwide lockdowns, the hospitality industry began its slow return to normal economic activity. In so doing, many hotels adopted greater social responsibility to reduce the risk of contagion (Gürlek & Kılıç, 2021), such as providing COVID-19 training and protective equipment for employees. Increasingly, given the lack of a reliable treatment for the illness or a successful vaccine, hotels began to consider the use of robots as a means of reducing the risk of virus spread. These decisions was not affected purely by supply forces. There were also demand factors at play here, with hotel services such as "*Hotel robots that can automatically spray disinfectant solution*" and "*five-minute room disinfection*" being increasingly sought by customers on the Ctrip platform.

More hotels and restaurants began deploying robots to provide "contactless services" (Zeng, Chen, & Lew, 2020). Despite these major technological changes affecting the hospitality industry, studies related to the impact of technologies and their acceptance by the general public remain somewhat scarce during major crises such as COVID-19, and especially with regards to contactless technologies. This research contributes to filling this knowledge gap by exploring changes in guest acceptance of hotel robots before and after COVID-19. The following questions were addressed: 1) Did the COVID-19 crisis have a significant effect on the acceptance of robots among hotel guests, and did guests have higher levels of acceptance of hotel robots after the initial COVID-19 outbreak was brought under control? 2) In what ways did COVID-19 affect guest acceptance of hotel robots? 3) How did different types of guests (such as by age and educational levels) affect acceptance and use of hotel robots? In addition to providing a novel contribution to knowledge, this work critically discusses potential avenues for further research on the topic.

Theoretical framework

Technology Acceptance Model

Research in social psychology has extensively referenced and used Fishbein and

Ajzen's theory of reasoned action to predict and understand motivational influences on behavior (Madden, Ellen, & Ajzen, 1992). TRA asserts that the most important determinant of behavior is behavioral intention (Montaño & Kasprzyk, 2015). It emphasizes that the behavior is controlled by the will, that is, the individual can exercise a great degree of control over behavior (Karnowski, Leonhard, & Kümpel, 2018). The Technology Acceptance Model (TAM) as proposed by Davis explains and predicts the usage of information technologies based on the theory of reasoned action (TRA) of Fishbein and Ajzen (1977). TAM was first proposed by Davis (1985) based on the assumption that people’s acceptance of information systems is determined by constructs that include perceived usefulness (PU) and perceived ease of use (PEOU).

Stock and Merkle (2017) defined robot acceptance as the extent to which users positively assess frontline service robots in terms of functionality and trustworthiness, and they developed the Robot Acceptance-Model (RAM). The current research posits that robot acceptance is not only about customer intentions to use robots, but also encompasses customer assessments in terms of perceptions, attitudes, and behavioral intentions. Zhong, Sun, Law, and Zhang (2020) used technology acceptance to investigate the impact of hotel robot services on consumer purchasing intentions through the experimental method. Ke, Lou, Tan, Wai, and Chan (2020) investigated the changes in technology acceptance among older people with dementia after directly interacting with humanoid social robots, and found that contact with robots changed perceptions related to their ease of use. Bröhl, Nelles, Brandl, Mertens, and Schlick (2016) extended TAM to robots, and found that the correlations among perceived usefulness, perceived ease of use, and behavioral intentions reached medium to high levels, indicating that TAM could be applied to human-robot interactions. In summary, it is appropriate to use TAM to study customer acceptance of robots. According to other factors such as the specific circumstances of the COVID-19 pandemic and robots, TAM was slightly modified for this research.

Perceived value theory

Perceived value is when consumers evaluate the utility of a product (or service) based on the perceptions of worth they receive (Zeithaml, 1988). Perceived value is a multi-dimensional concept that covers many aspects (Chuah, Aw, & Cheng, 2021). Sheth, Newman, and Gross (1991) conceptualized customer value in five dimensions: function, emotion, society, cognition, and conditional values. Sweeney and Soutar (2001) found the value of consumer durable goods to be emotional, social, quality/performance, and value for money. Perceived value affects consumer behavior. Vishwakarma, Mukherjee, and Datta (2020) applied a value adoption model and found that perceived value was the most important predictor of the use of virtual reality (VR).

Perceived value has begun to be used in research on hotel robots. Perceived value represents the benefits of social robotics in providing higher service quality (de Kervenoael, Hasan, Schwob, & Goh, 2020). Hu (2021) divided perceived value into perceived utilitarian value and perceived hedonic value, and pointed out that the impact of perceived hedonic value on user attitudes depends on perceived utilitarian value. Perceived utilitarian value refers to the overall evaluation of the functional benefits and utility produced by a consumer experience (Babin, Darden, & Griffin, 1994), and is considered to be a key factor influencing consumer choice (Sweeney & Soutar, 2001). Especially in the situation of COVID-19, customers placed more emphasis on the perceived utilitarian value of robots. Therefore, this study selected the utilitarian aspect of perceived value in completing the research.

The great disaster and human intentions

Although it has been argued that the global impact of one of COVID-19's precursors - SARS - was limited in terms of health outcomes (Beutels *et al.*, 2009), the scale of its macroeconomic impact was considerable, especially in tourism, air transportation and investment (Hai, Zhao, Wang, & Hou, 2004; Keogh-Brown & Smith, 2008). People's fear of SARS changed lifestyles and attitudes, albeit in an ephemeral manner, reducing levels of shopping, social activities and business travel, while increasing employment pressures (Lee & Warner, 2006). Similarly, the resulting impact of the H1N1 epidemic on tourism and hospitality was considerable, with a very negative effect on travel intentions (Li, Nguyen, & Coca-Stefaniak, 2020). One of the more positive outcomes which could be inferred from this outbreak was that people were willing to change their behaviors to avoid infection, subject to the delivery of accurate information. Therefore, customer acceptance of hotel robots might be influenced by a major crisis such as COVID-19.

With COVID-19, more people realized the potential value of contact-free services, with many willing to engage with such technologies. Technological innovation can become a critical factor for hotel risk management and may affect customer perceptions related to health risks (Shin & Kang, 2020). Robots are an important innovation within contactless technology. A study by Romero and Lado (2021) found that guests were prone to believe that robots reduced the risk of infection in hotels and the preventive effect of robots led to higher levels of intentions related to new customer bookings. Kim, Kim, Badu-Baiden, Giroux, and Choi (2021) pointed out that in health-related crises (such as COVID-19), customer preferences for robots increased because the use of service robots reduced the possibility of infection. However, Seyitoğlu and Ivanov (2021) argued that service robots create a technical barrier between tourists and employees, increasing the physical and emotional distance. However, a study by Odekerken-Schröder, Mele, Russo-Spena, Mahr, and Ruggiero (2020) found that robots could be used to alleviate people's loneliness. All in all, it is becoming increasingly apparent that COVID-19 has resulted in significant changes in people's perceptions about the use of robots for the delivery of services.

Hypotheses

Usefulness

Perceived usefulness has been defined as the degree to which people think that using a system will improve job performance (Davis, Bagozzi, & Warshaw, 1989). For example, chatbots and other technologies have started to make travel easier by helping visitors plan or solve on-site problems (Pillai & Sivathanu, 2020). A more recent quantitative study by Siderska (2021) established that the usefulness of robots since the onset of COVID-19 was considered to be substantial. In addition, people thought robots could reduce the risk of infection (Romero & Lado, 2021). When confronted with a major epidemic, customers are likely to perceive robots as especially useful and so the effect of usefulness on attitudes increases. In line with this, the following hypothesis was formulated:

- H_1: The impact of usefulness on attitudes will be higher after COVID-19

Ease of use

Perceived ease of use refers to the degree to which a person thinks that using a system will be effortless (Davis *et al.*, 1989). More hotels deployed robots during COVID-19 (Kim *et al.,* 2021). However, the performance of artificial intelligence robots was not satisfactory in all cases (Go, Kang, & Suh, 2020). During operations, customers encountered various technical problems, such as how to open the correct storage locations when the robot delivered items (de Kervenoael et al., 2020). Customers needed to expend extra energy to interact with robots, which made them have to pay more attention to the ease of use of robots. Thus, given the COVID-19 situation, the following hypothesis was proposed:

- H_2: The impact of ease of use on customer attitudes will be higher after COVID-19
- H_3: The impact of ease of use on usefulness will be higher after COVID-19

Anthropomorphism

Anthropomorphism is defined as the attribution of human-like characteristics, behaviors, or mental states to non-human entities, such as objects, animals, and recent technological equipment (Pelau, Dabija, & Ene, 2021). Anthropomorphic design affects people's perceptions of robots (Zhu & Chang, 2020). The use of anthropomorphic robots in tourism may result in enhanced experience value (Christou, Simillidou, & Stylianou, 2020). When customers think that robots can understand them just like real humans, they tend to perceive robots as being more valuable. Customers get frustrated and angry when chatbots do not understand their questions (Castillo, Canhoto, & Said, 2020). On this basis, the following hypothesis was developed:

- H_4: The impact of anthropomorphism on value among hotel customers will be higher after COVID-19

Social influence

Social influence is defined as the degree to which an individual’s attitudes or behavior is influenced by others (Ivkov, Blešić, Dudić, Pajtinková Bartáková, & Dudić, 2020). In the consumer decision-making process, friends and family members provide reliable sources of information (Gursoy, Del Chiappa, & Zhang, 2018). During COVID-19, more people used hotel robots and developed positive attitudes towards them because the robots reduced the risk of infection (Romero & Lado, 2021). If the customer's social networks (such as friends, colleagues, family members) are in favor of AI devices during service, the use of AI devices enhances social identity (Gursoy, Chi, Lu, & Nunkoo, 2019). Therefore, social norms during COVID-19 should have a greater impact on consumers. The more positive the social impact, the more positive would be the customer perceived value of robots. On this basis, the following hypothesis was formulated:

- H_5: The impact of social influence on value will be higher after COVID-19

Attitudes

The risk of infection affected customer attitudes towards hotels that offered robots as part of their services (Galoni, Carpenter, & Rao, 2020). Given that robots are considered to be less likely to transmit pathogens, travelers tended to be more likely to have positive mindsets towards hotels equipped with robots (Kim et al., 2021). According to the Theory of Reasoned Action, people's attitudes can significantly influence their behavioral intentions (Fishbein & Ajzen, 1977; Shin & Jeong, 2020). As a result of COVID-19, hotel customers generally developed more positive attitudes towards interacting with robots, which resulted in higher booking intentions (Romero & Lado,

2021) and payment fees (Chuah et al., 2021). In line with this, the following hypothesis was specified:

- H_6: The impact of attitudes on behavioral intentions will be higher after COVID-19

Value

One of the motivating factors for the hospitality industry to adopt smart technologies is to reduce costs and improve efficiency (Belanche, Casaló, Flavián, & Schepers, 2020b; Gretzel, Sigala, Xiang, & Koo, 2015). In addition, customers generally tend to think that robots can provide a more standardized service (Belanche, Casaló, Flavián, & Schepers, 2020a). During the COVID-19 pandemic, robots were often given more dangerous tasks to deliver (Chuah *et al.*, 2021), which contributed to a reduction in customers' perceptions of the risks involved, especially as regards infection (Romero & Lado, 2021). Therefore, during COVID-19, a perception developed among customers that robots were able to offer better value in hotel settings. In line with this, the following hypothesis was proposed:

- H_7: The impact of value on behavioral intentions among customers will be higher after COVID-19

Behavioral intentions

Behavioral intentions clarify and envision the acceptance among users of new technologies (Pillai & Sivathanu, 2020). Based on TAM, this study argues that people tend to be rational. In line with this, and as a result of a pragmatic approach, Romero and Lado (2021) showed that after a major public health crisis, people tend to be more inclined to accept the advantages of contactless services. As a result of this, the acceptance of contactless services is likely to grow as a pandemic continues, which led to the following hypothesis:

- H_8: Customers' behavioral intentions will be higher after COVID-19

Methods

The sample for this research included Chinese hotel guests before and after COVID-19. Some 247 responses were obtained before the outbreak, with a response rate of 87.85%. After COVID-19, 601 responses were collected, with a response rate of 86.19%. The pre-epidemic questionnaire was administered from January 14 to 23, 2018. The post-pandemic questionnaire was run when the situation in China was largely under control. Several hypotheses were developed and empirically tested adopting a pseudo-experimental design, as shown in the proposed conceptual model (Figure 1).

[Insert Figure 1 here]

Online questionnaires were used to collect the data, using China's largest questionnaire platform Questionnaire Star (https://www.wjx.cn/). The two surveys were carried out using snowball sampling, collected by reposting in WeChat groups and Moments. The questionnaire was translated into Chinese for the convenience of the participants. As part of this process, participants were asked to watch a video online of a hotel robot. This video was on a separate page and required mandatory viewing. Only after watching the video could people move to answering the section on the next page.

Once they had done this, they were directed to complete questionnaires, which were divided into two parts. The first part included questions related to the respondent's demographic profile and hotel use information (e.g., gender, age, education). The second part focused on respondent acceptance of robots in hotels, including constructs such as usefulness, ease of use and attitudes. The measurement scales contained a total of 21 items. All questions were measured on five-point Likert-scales (1 = strongly disagree; 5 = strongly agree). The data were analyzed using regression-based Partial Least Squares Structural Equation Modeling (PLS-SEM), with SPSS 21.0 and SmartPLS 3 software used for processing and analysis. The partial least squares method does not have strict normal distribution requirements for the data, and it is also applicable in the case of small samples (Hair, Risher, Sarstedt, & Ringle, 2019).

Results

Descriptive statistical analysis

The demographic profile of respondents is summarized in Table 1. Most respondents post-COVID-19 (67.6%) had attained a university degree or above (e.g., postgraduate diploma). This proportion was 72.4% among respondents in the pre-COVID-19 survey. Pre-COVID-19, 90.3% of the respondents had never used a hotel robot, but this proportion dropped to 76.9% after COVID-19. The penetration rate of hotel robots increased significantly following the outbreak of COVID-19 (i.e., from 9.7% to 23.1%). Some 80.2% of respondents' annual incomes were less than $21,000 dollars after COVID-19. This distribution was broadly in line with China's annual income data.

[Insert Table 1 here]

Measurement and structural model

This study first conducted the Harman (1967)' s single factor test to check whether the data set had common method bias problems. Exploratory factor analysis through SPSS found that the variance contribution rate of the first factor was less than 50%, which fit the requirements (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). In addition, a variance inflation factor (VIFs) analysis was conducted on all latent variables in the research model, and the results showed that the VIFs of all variables were less than three, so the model had no common bias problem (Kock, 2015).

Then, according to Anderson and Gerbing's (1988) method of testing the measurement model, a confirmatory factor analysis was conducted. First, the reliability, combination validity and aggregate validity of the measurement model were tested (Hair, Sarstedt, Ringle, & Mena, 2012). The measurement results are shown in Table 2. The standardized factor loadings of all items were greater than 0.7, and the combined reliability of all constructs was greater than 0.7, indicating that there was good measurement reliability (Hair et al., 2019). In addition, as with de Kervenoael et al. (2020), because the factor loading of just one item does not meet the requirements, a minimum of two items was selected for measurement. The average variance extraction of all constructs was greater than 0.5, indicating that there was good convergent validity (Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018). This indicated that all measurement items could well explain their corresponding constructs.

[Insert Table 2 here]

Then, according to the recommendations of Fornell and Larcker (1981), the discriminant validity of the measurement model was tested, and the measurement results are shown in Table 3. The square roots of AVE of all constructs were greater than the correlation coefficients between the construct and other constructs, showing good discriminant validity. As for content validity, usefulness measured whether robots met the needs of customers. Ease of use was a measure of how easy it was to use hotel robots as perceived by customers. Attitudes expressed customer views on robots. Anthropomorphism was a measure of perceptions of the humanoid features of robots. Social influence was the degree to which customers were affected in the use of robots by important people around them. Value was the functional value of the robot as perceived by customers. Behavioral intentions expressed the willingness to choose robot hotels again in the future. The measurement model met the requirements of the scale design and could be used as a measurement tool for this hotel robot acceptance research.

[Insert Table 3 here]

The fit of the model was then tested. The analysis results showed that R^2 (usefulness) = 0.309, R^2 (attitudes) = 0.627, R^2 (value) = 0.372, and R^2 (behavior intentions) = 0.593. The overall model fit well, and the model construction was acceptable (Ringle, Wende, & Becker, 2015). Then, PLS and Bootstrapping methods were used to test the structural model, and Bootstrapping = 5,000 was selected. Bootstrapping is a non-parametric test method that resamples the original data. It estimates the path standard error and t-value of the structural model to calculate the significance of a path (Chin, Marcolin, & Newsted, 2003).

Hypothesis path testing

The results for the post-COVID-19 survey are shown in Table 4 and Figure 2. Figure 3 shows the results before COVID-19. A comparison of the survey data pre- and post-COVID-19 demonstrated that the impact of usefulness on attitudes after COVID-19 increased, and thus H_1 was supported. The impact of ease of use on attitudes weakened, therefore, H_2 was not supported. The impact of ease of use on usefulness increased, thus H_3 was supported. The impact of anthropomorphism on value weakened, thus H_4 was not supported. The impact of social influence on value increased, thus H_5 was supported. The impact of attitudes on behavioral intentions increased, thus H_6 was supported. The impact of value on behavioral intentions increased, and H_7 was supported. Also, through an independent sample t-test, it was found that the intention to use hotel robots post-COVID-19 was higher, and this was statistically significant; so, H_8 was supported. People's acceptance of robots increased psot-COVID-19.

[Insert Table 4 here]

[Insert Figures 2 and 3 here]

The indirect effect calculation between each variable and the independent variables was performed based on the path coefficients. The results (Table 5) indicated that the degree of influence of the six variables on guest behavioral intentions was: attitudes > usefulness > ease of use > value > social influence > anthropomorphism. Therefore, the most influential factors were attitudes, usefulness, and ease of use.

[Insert Table 5 here]

Hypothesis testing of moderating variables

Since the moderating variable adopted was categorical, group regression analysis was used to verify its regulating role. After excluding the analysis results without significant adjustment effects (the judgment criterion was that the significant F change value of all equations was less than 0.05, which meant passing the hypothesis test), the analysis results with significant adjustment effects are shown in Table 6.

[Insert Table 6 here]

Based on this analysis, the proposed model was revised, as shown in Figure 4. The revised model eliminated the adjustment variables that had no significant effect on cognitive variables, and reflected the influence of gender, age, whether a hotel robot had been used, and whether other robots had been used by respondents. The model applicable to the pre-COVID-19 survey results is shown in Figure 5. Post-COVID-19, there were more adjustment variables. Then, gender regulated the path of usefulness to attitudes, with men caring more about usefulness than women. Regardless of before or after COVID-19, previous experience with hotel robot services was an important moderating variable. Customers who had used hotel robot services cared more about their ease of use. This was mainly because people had experiences of the easy or difficult in operating robots, so they paid more attention to ease of use. Regardless of gender and prior direct experience with hotel robots, COVID-19 resulted in many people having to become familiar with new technologies, which may have affected their level of acceptance of technology.

[Insert Figures 4 and 5 here]

Conclusions, discussion, and implications

This research investigated guest acceptance of hotel robots in China before and after COVID-19. It also explored whether the pandemic affected the acceptance of hotel robots. The results showed that most of the path coefficients increased post COVID-19, whilst others decreased. That is to say, COVID-19 changed people's perceptions of and behavior towards service robots. The following main conclusions were drawn:

(1) Post-COVID-19, the impact of hotel robot usefulness on attitudes increased, whilst ease of use on attitudes reduced. This demonstrated that customers thought that the usefulness of the robot was more important than the ease of use, which corresponds with the findings of Siderska (2021). Especially with COVID-19, robots as a contactless service providers greatly reduces the perceived risk of infection (Romero & Lado, 2021). However, the importance of ease of use on attitude decreased. During COVID-19, customers encounter various problems with robot operation (de Kervenoael et al., 2020). However, even if there were operational problems, customers persisted with robot use. Being rational, they were willing to work hard to learn how to use robots. Overall, the results suggest that the attitudes and behavioral intentions of past and potential hotel guests towards robots and the services they can provide are changing. Whether this change is purely ephemeral and motivated by a pragmatic stance triggered COVID-19 (i.e., risk of infection from human-to-human customer service) remains to be established.

(2) The impact of anthropomorphism on value decreased, but the social influence

on value increased. After COVID-19, the importance of whether robots were like humans and whether they could understand human emotions was less. Post-COVID-19, no matter whether the robot was human-like or non-human-like, as long as it could provide good services (such as reducing the risk of infection and with high service efficiency), customers considered the robots to be valuable. In addition, surrounding people (e.g., friends, family) had a greater impact on the perceived value of the robot. Post-COVID-19, more people used hotel robots and developed mor positive attitudes towards robots due to their reducing the risk of infection (Romero & Lado, 2021). When people around the customer hold more positive attitudes towards AI devices, customers are more likely to feel that AI produces more benefits (Gursoy et al., 2019), and therefore believe that AI has greater value.

(3) The impact of attitudes on behavioral intentions and value on behavioral intentions increased. Also, behavioral intentions increased post-COVID-19. Guests will actively seek new opportunities to interact and communicate with robots (Tung & Au, 2018). The more extensive the customer positive engagement with robots, the more willing they were to experience robots again. Also, the impact of perceived value on behavioral intentions increased. Post-COVID-19, whether robots could provide efficient services greatly affected customer use intentions. The intentions to use robots increased, which means that customer acceptance of hotel robots grew. This is consistent with the findings of Romero and Lado (2021) that customers believed that robots reduced the risk of infection within hotels, so the preventive effect of robots stimulated a higher willingness to book.

This research explored changes in people's acceptance of hotel robots in China pre- and post-COVID-19 to address a current knowledge gap related to the impact of major crises on technology acceptance. The results show that people's acceptance of robots significantly changed due to COVID-19. Thus, a major crisis can change customer attitudes and behaviors toward new technologies, which supports the results of Kim et al. (2021).

Second, most of the research related to tourism technology under COVID-19 adopts qualitative methods (Christou et al., 2020; Zeng et al., 2020). Some quantitative studies have confirmed that COVID-19 impacts customer robot preferences from the perspective of risk perceptions (Kim et al., 2021). However, there is no research to explore the specific impact mechanisms from a theory point of view. This investigation applied the Technology Acceptance Model to explore in detail the impact of COVID-19 on the usefulness and ease of use of hotel service robots, which differed from previous research. This work is a good example of using quantitative methods to investigate the impact of crisis events on user acceptance of artificial intelligence.

Third, this research explains the paths through which major crises affect customer acceptance of technology. Most previous studies used ANOVA to contrast variables (Kim et al., 2021) and few studies compared paths. This research provides a useful case example of using path comparison. It was found that most path coefficients increased post-COVID-19, and others decreased, and reasons for the changes were explained.

In addition, this research represents a novel extension of the technology acceptance model, and can provide a useful reference for new technology-related analyses. This research also provides suggestions for further scholarly inquiry in this context as well as the development of robot service technologies in the hospitality industry.

The findings may offer practical enlightenment for robot manufacturers and hotel managers. For robot manufacturers, the more positive interactions between customers and robots, the stronger the willingness to use them. According to involvement theory (Huang, Chou, & Lin, 2010), the more customers invest in robots, the more they will have deeper emotions for them. As a result, robot manufacturers should add more interactive parts to their programs so as to increase customer engagement. In addition, this research found that guests who have used hotel robots before are more concerned about the ease of use of robots. With the increasing popularity of robots, more customers have used robots. Therefore, robot manufacturers should continuously improve robot systems to make them more human-machine friendly and easier to operate. As a result, customers will generally have more positive attitudes towards robots and be more willing to experience robot services.

For hotel managers, this research has demonstrated that people's acceptance of robots increased after COVID-19 and the pandemic has accelerated technological innovation. Therefore, more hotels should consider deploying robots to reduce the risk of infection post-epidemic, and also as an attraction to attract customers. Gender and age levels affect the acceptance of robots, so hotels need to establish customer profiles based on customer characteristics and provide customized services for different guests. Deploying robots in hotels is only the first step. More importantly, robots should be more attractive and useful for customers. This depends not only on the appearance and programming of robots, but also on the service environment in which they operate (Choi, Mattila, & Bolton, 2021). When customers have more positive attitudes towards robots, their intentions to use them are stronger. Therefore, hotel managers should implement a series of measures to enhance customer attitudes about robots. For example, pleasant demo videos can familiarize customers with digital services and lower the barriers to technology adoption (Choi, Mehraliyev, & Kim, 2020). Demonstration videos watched before operating robots will increase positive attitudes toward their use.

Limitations and future research directions

First, this research used a video portraying robot offering services within a hotel environment to help respondents visualize the concept being tested. Although this was a necessity given the low proportion of respondents who had actually experienced first-hand what it is like to be serviced as a customer by a robot, as the proportion of people more familiar with this grows, so will the validity and depth of the insights of future editions of this study.

Second, Go et al. (2020) found that using only the extended TAM model might be insufficient for measuring the direct effects of the types of AI robots and machine learning applications on interactions and consumer perceptions. The perceived risk of COVID-19 has had a positive impact on customer interaction with robots (Wu, Zhang, Zhu, & Yu-Buck, 2021). In the future, other theories and variables should be considered, such as perceived risk.

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