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Benefit-triggered or trust-guided? Investigation of customers' perceptions towards AI-adopting hotels amid and post COVID-19 pandemic

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Abstract
This research exhibits and empirically validates an expansion of the Unified Theory of Acceptance and Use of Technology (UTAUT2) and integrates artificial intelligence (AI) and pandemic threats to explain customers' utilitarian-versus-emotional behavioral intentions towards AI-adopting hotels amid and post-COVID-19. Utilizing data gathered from 416 customers, the findings confirmed that customers' perceived importance of AI amid and post-COVID-19 has a direct positive effect on their behavioral intentions towards hotels adopting those technologies, with perceived benefits of technology playing a more significant mediating role than customers' trust intervening in that correlation. This provides evidence for the utilitarian perception of customers during crises and offers updated insights into the dynamics that constitute and trigger hotel customers' behavioral intentions toward AI. The results provide hoteliers with a valid understanding and rationalization of how to utilize AI to address customers' crucial concerns and interests amid and post-COVID-19 and in similar crises.

Keywords
Artificial intelligence, behavioral intentions, customer trust, perceived benefits, UTAUT2

Introduction

Artificial intelligence (AI) has been widely used in the contemporary hospitality industry and is deeply changing and reshaping the behaviors and experiences of both tourists and businesses (Zhong et al., 2020; Ivanov et al., 2020; Gursoy and Chi, 2020; Kim et al., 2021; Knani et al., 2022; Saydam, et al., 2022; Li, et al., 2022). From the perspective of hospitality businesses, as the supply side, the adoption of AI solutions improves service quality while increasing operational capability and efficiency, lowering costs, and consequently creating a competitive advantage (Lukanova and Ilieva, 2019). While providing interactive,

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personalized, and customized services to tourists can improve the customer experience (Lu, 2019), it cannot improve the supply side. AI frequently refers to machine learning, deep learning, robotics, the Internet of Things, and the use of big data (Lukanova and Ilieva, 2019). In hospitality companies, AI offers versatile applications, like biometric authentication (hence, biometrics), robotic process automation, virtual and augmented reality, self-service technologies, and so forth (Ivanov et al., 2020; Tussyadiah, 2020). AI applications are used to authenticate online bookings and check-in/out, access guestrooms and outlets, operate in-room functions, process inquiries and payments, facilitate luggage transfer, provide concierge services, clean and disinfect guestrooms and public areas, deliver foodservice, and pose as in-room assistants (Murphy and Rottet, 2009; Lukanova and Ilieva, 2019; Ivanov et al., 2020). However, there are some risks associated with tourists' distrust, fear of interacting, security and privacy concerns, and human contact preferences (Tussyadiah, 2020; Li et al., 2022; Saydam et al., 2022; Knani et al., 2022).

Moreover, the hospitality industry is highly vulnerable to outbreaks of epidemics and diseases (like COVID-19, SARS, H1N1, MERS, Ebola, etc.), which severely damage the industry and deeply affect the behaviors and experiences of both tourists and businesses in terms of safety, economic spending, conviction, and attitude (Ivanov et al., 2020; Zeng et al., 2020; Lin, Chi, & Gursoy, 2020; Kim et al., 2021). Particularly, the COVID-19 pandemic has urged the hotel industry to accelerate the exploitation of AI-contactless solutions to recover customer trust and encourage demand through keeping social and physical distance and lowering costs (Seyitoğlu and Ivanov, 2020; Romero and Lado, 2021; Perić, and Vitezić, 2021; Kim et al., 2021). Hence, increasing interest is directed toward investing in and adopting AI and its applications in hospitality enterprises to enrich the customer service experience and minimize pandemic-related health and economic risks (Ivanov et al., 2020; Gaur et al., 2021).

Since AI solutions, in conjunction with the COVID-19 pandemic, have reformed customers' attitudes, expectations, and experiences, hotel marketers and operators must have a thorough understanding of their acceptance of such trends, particularly during and after the COVID-19 pandemic (Lin et al., 2020; Ivanov et al., 2020; Gaur et al., 2021; Lin et al., 2020; Perić, and Vitezić, 2021). Yet, there is a lack of empirical research on the role of AI to manage safety and health risks in hospitality settings amid and post-pandemic era (Ivanov, et al., 2020; Zhong et al., 2020; Zeng et al., 2020; Seyitoğlu and Ivanov, 2020). Accordingly, hospitality scholars have called for further research to understand the role of AI contactless solutions to assure and recover customer trust and safety amid and post-pandemic era (Hao et al., 2020; Romero and Lado, 2021; Pillai et al., 2021; Perić, and Vitezić, 2021; Lin et al., 2020; Gaur et al., 2021). There is no empirical study that investigates whether the COVID-19 pandemic obliges intelligent automation of hotel services, and there is also no dedicated investigation of whether customers embrace utilitarian or emotional perspectives towards staying in hotels during and post-COVID-19 and towards newly introduced initiatives.

This research thus aims at determining how the pandemic compels hotel customers' utilitarian versus emotional tendencies and their behavioral intentions toward AI-adopting hotels. Working towards that aim, this study employed a noteworthily extended utilization of Venkatesh et al. (2012)'s unified theory of acceptance and use of technology 2 (UTAUT2) to examine whether customers embrace utilitarian or emotional perspectives towards staying in hotels amid and post-COVID-19. That is, the literature still needs more studies that integrate customer trust, in addition to novel variables, into UTAUT2, in order to gain more structured, meaningful outcomes. There are limited studies that involved customers' trust to reveal their behavioral intentions in the hospitality context in general (Jalilvand et al., 2017) and amid and post-pandemic in particular (Hao, 2021; Park and Tussyadiah, 2020; Ruan et al., 2020; Tussyadiah et al., 2020; Perić and Vitezić, 2021). The authors therefore adopted the perspective of Hao (2021), who perceived that some contactless technologies might provoke some uncertainties and trust issues among customers. Consequently, trust occupies an essential position and represents a focal addition to UTAUT2 in the current study's aim to inquire whether hotel customers are more inclined to be utilitarian or emotional.

The concepts of utilitarian versus emotional nature are comparable and equivalent to UTAUT2's variables, and are most suitable to the current study's objective. Hence, twofold purposes are attained. In addition to the intervening function of AI benefits, the model extends to examine the intervening and mediating role of "COVID-triggered customers' trust in AI-adopting hotels" (hence, trust) towards their behavioral intentions. Trust represents a customer's emotional perspective. To provide a more thorough comprehension of the role of technologies, probable moderating variables need to be investigated (Beatson, 2010; Salem & Čavlek, 2016). To recapitulate, extending the UTAUT2's variables has the evident benefits of enriching the UTAUT2's current stand by a novel set of variables that have not been included in the model before, suiting the current study's needs and aims that would not otherwise be attained if UTAUT2 is utilized as it is, and, eventually, providing a solid base for future research endeavors to build upon for unreservedly integrating more contemporary variables, while simultaneously enjoying the well-structured skeleton of UTAUT2.

Thus, unlike the original UTAUT2 model, the current study's UTAUT2 equivalents of habit, social influence, and facilitating conditions will not act as independent variables, but rather will be scrutinized as moderators (as shown in Figure 1). This study and its proposed extended model will thus direct hoteliers in predicting customer trends concerning AI in hotels and in formulating and implementing effective strategies for the adoption of AI technologies during pandemic periods and similar crises.

Literature review and hypotheses development

AI importance and Behavioral Intentions (BIs)

Behavioral Intentions (BIs) refer to an individual's likelihood of engaging in a specific behavior, which helps to predict the actual behavior in one's decision-making process (Ajzen, 1991). Based on the Theory of Planned Behavior (Ajzen, 1991) and the Theory of Reasoned Action (Fishbein and Ajzen, 1977), prior studies have extensively confirmed that customer awareness and attitudes towards novel technology usage and importance have an influence on BIs (e.g., Shin and Kang, 2020; Zhong et al., 2020; De Kervenoael et al., 2020; Kim, et al., 2021). Shin and Kang (2020) revealed that lower expected interaction and better cleanliness associated with technology innovation positively affected hotel booking intention during the COVID-19 pandemic. The importance of personalization and entertainment, as well as the safety and security of smart hotels, had a leading role to shape customer behavior (Elkhwesky et al., 2022; Kim et al., 2021). Moreover, UTAUT2-based previous findings performance expectancy has significant effect on attitudes and intentions to use various innovative technologies (Chen et al., 2022; Hao, 2021; Jung and Cha, 2022; Morosan and DeFranco, 2016; Wu, et al., 2021). Thus, the AI importance' (UTAUT2's performance expectancy) role in shaping customers' BI is evident. As such, we propose:

H1: AI-importance has a positive and significant influence on BIs.

AI-importance and customer trust

COVID-19-provoked anxiety was a positive predictor of attitude towards virtual reality tourism (Talwar, et al., 2022). Empirical research emphasized that intelligent technologies, including AI, serve as objects of customer trust (Tussyadiah et al., 2020). Ruan et al. (2020) similarly showed that technological proficiency and service innovation accomplishment positively affect

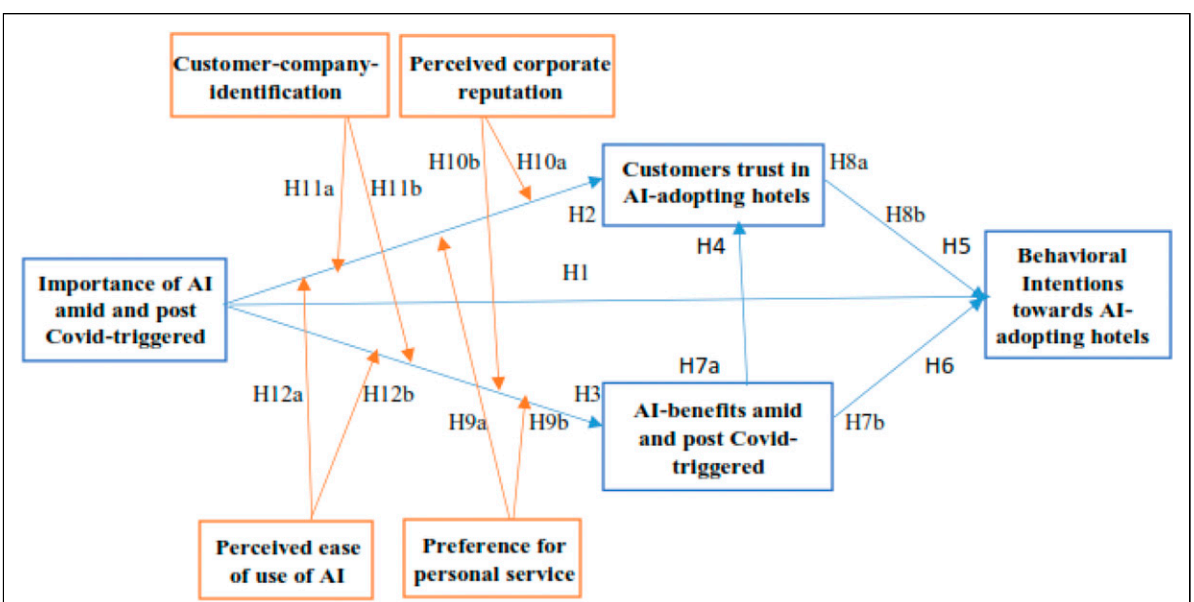

Figure 1. Conceptual model.

trust by customers' perceived value. Based upon the interdisciplinary trust model proposed by McKnight and Chervany (2001), a series of studies identified that trust propensity has positive influences on developing trust beliefs toward intelligent technologies (e.g., Tussyadiah et al., 2020). Thus, the following hypothesis is proposed:

H2: AI-importance has a positive and significant influence on customer trust.

AI-importance and AI-benefits

Several studies confirmed the positive effect of AI perceived importance (UTAUT2's performance expectancy) on AI-benefits (UTAUT2's effort expectancy) in the hospitality context (De Kervenoael et al., 2020; Ruan et al., 2020; Shin and Kang, 2020; Tussyadiah, 2020). In addition, Shin and Kang (2020) found that minimized interaction and high cleanliness associated with new technologies positively affected perceived health risks during the COVID-19 pandemic. Likewise, de Kervenoael et al. (2020) confirmed that robot characteristics positively affect AI perceived benefits. As such, and as a variation of UTAUT2, it is proposed that:

H3: AI-importance has a positive and significant influence on AI-benefits.

AI-benefits and customer trust

Prior studies collectively established that the AI-benefits (UTAUT2' effort expectancy) play an important positive role in forming customers' perceived trust (Ameen, et al., 2021; Lee and Lee, 2019; Ruan et al., 2020). Specifically, Ameen et al. (2021) demonstrated the positive effect of perceived convenience and AI-enabled service quality on trust. Pai et al. (2018) confirmed that biometric technology benefits positively affected visitors' perceptions of trust. Ruan et al. (2020) showed that customers' perceived value of technological competence and service innovation implementation positively affect trust. Therefore, it is assumed that:

H4: AI-benefits has a positive and significant influence on customer trust.

Customer trust and Behavioral Intentions (BIs)

Trust has been shown to be a strong determinant of BIs (e.g., Tussyadiah et al., 2020; Park and Tussyadiah, 2020; Ruan et al., 2020; Lee and Lee, 2019). Customer trust, as perceived by Martínez and Del Bosque (2013), represented a necessity for the healthy relationship with the hotel, represented in creating a positive attitude, loyalty, and satisfaction. Also, Cha (2020) confirmed that perceived trust has a significant positive effect on the intention to use restaurant robots, and Pai et al. (2018) found that perceived trust has a positive impact on the intention to use the biometric systems in the hospitality industry. Based upon the trust model proposed by McKnight and Chervany (2001), other studies supported the positive relationship between trust and positive intentions towards AI and service robots (Tussyadiah et al., 2020; Park and Tussyadiah, 2020). Consistently, the above studies supported the notion of the theory of planned action (Ajzen, 1991), implying that beliefs, particularly trust, are directly associated with corresponding intentions. Consequently, it is proposed that:

H5: Customer Trust has a positive and significant influence on BIs.

AI-benefits and Behavioral Intentions (BIs)

In UTAUT2, AI-benefits, current study's equivalent of effort expectancy, directly affect customers' intentions towards new technological adoption (Jung and Cha, 2022). Consistently, AI-benefits are extensively researched to ascertain their positive effect on customers' behaviors and attitudes, for instance, towards using social robots (De Kervenoael et al., 2020), for service robots in restaurants (Jung and Cha, 2022), and for touchless, mobile-phone-based payment in restaurants (Chen et al., 2022). Lin et al. (2020) highlighted that robots' benefits support customers' positive emotions toward AI robotics. As such, it is hypothesized that:

H6: AI benefits have a positive and significant influence on BIs.

The mediating effects of perceived AI-benefits

Previous studies established that customers first need to perceive a novel technology application as beneficial to develop positive behavioral intentions towards it. AI-benefits worked as a mediating variable in the relationship between both AI technology and trust (Lee and Lee, 2019). Ruan et al. (2020) revealed that perceived value mediated the association between both technological provision and trust, and between service innovation accomplishment and trust.

Pinxteren et al. (2019) exhibited that the influence of perceived trust on customers' intentions to use humanoid service robots was fully mediated by customers' perceived enjoyment. AI benefits' mediating is thus recognized to influence the relationship among technological novelties and customers' reactions, suggesting the subsequent hypotheses:

H7a: AI-benefits positively and significantly mediate the relationship between AI-importance and customer trust.
H7b: AI-benefits positively and significantly mediate the relationship between AI-importance and BIs.

The mediating effects of customer trust in AI-adopting hotels

Relevant studies supported trust as a mediator between AI importance and AI-benefits (Ameen et al., 2021; Ruan et al., 2020), as well as mediating the AI benefits correlation to behavioral intentions (Wang, et al., 2015; Lee and Lee, 2019). Ruan et al. (2020) revealed that trust mediates both the relationship between perceived value and brand image, and between perceived value and perceived quality. Ameen et al. (2021) found that trust also mediates the effects of convenience, personalization, and AI-enabled service quality on AI-enabled customer experience. Lee and Lee (2019) proved that brand trust mediates the relationship between customers' engagement with branded hotel applications and brand loyalty. Thus, this efficaciously mediating role of trust is consistent with the trust model (McKnight and Chervany, 2001), suggesting the subsequent hypotheses:

H8a: Customer trust positively and significantly mediates the association between AI-importance and BIs.
H8b: Customer trust positively and significantly mediates the association between AI-benefits and BIs.

The moderating effect of preferences for personal service (personal-service)

Preferences for Personal Service (hence, personal-service) refers to the desire to interact with service employees during the service encounter (Dabholkar and Bagozzi, 2002). The influences of customers' preferences for personal service, as the UTAUT2's "Habit," have been highlighted in previous studies, on customers satisfaction and, hence, commitment, (Beatson, 2010), and intentions (Chen et al., 2022; Gupta et al., 2018; Morosan and DeFranco, 2016). Prior studies provided empirical evidence of the negative link between personal-service and the benefits of technology (Ameen et al., 2021) and customer AI-related trust (Tussyadiah et al., 2020). For illustration, Shin and Kang (2020) exhibited a positive effect of expected interaction with employees on the perceived health risk of hotel customers during the COVID-19 pandemic. Ameen et al. (2021) demonstrated that perceived sacrifice due to a lack of human interaction has a negative direct effect on AI-enabled customer experience. It has been even reported that self-service represents a significant moderating pose in technology-related models (Beatson, 2010; Dabholkar and Bagozzi, 2002). The moderating role of personal-service is predicted, proposing the following hypotheses:

H9a: Personal-service positively and significantly moderates the impact of AI-importance on customer trust.
H9b: Personal-service positively and significantly moderates the impact of AI-importance on AI-benefits.

The moderating effect of perceived corporate reputation

Perceived Corporate Reputation (hence, reputation, resembling UTAUT2's "Social Influence") is defined as the customer's overall evaluation of the organization's past actions and expectations regarding its future actions, in view of its efficiency in relation to the main rivals (Walsh et al., 2009). Prior studies provided empirical evidence on the positive influence of reputation on trust in tourism and hospitality contexts (e.g., Jalilvand et al., 2017; Chang, 2013). Moreover, reputation has a significant impact on AI-benefits; represented as perceived value, service quality, satisfaction, and perceived trust (Perez-Aranda, et al., 2019; Chang, 2013; Dardeer et al., 2017). Thus, customers who perceive a hotel as being highly reliable are most likely to develop trust and a more positive perception of acquired AI-benefits. With this situation, and the pre-hypothesized impact of AI importance on trust and AI-benefits, the moderating role of reputation is predicted, proposing the following hypotheses:

H10a: Reputation positively and significantly moderates the impact of AI-importance on customer trust.
H10b: Reputation positively and significantly moderates the impact of AI-importance on AI-benefits.

The moderating effect of perceived customer-company identification

Perceived Customer-Company Identification (hence, identification, representing UTAUT2's "Social Influence") is defined as the extent to which customers perceive the company identity as trustworthy (Bhattacharya and Sen, 2003). Identification positively pushes towards customer loyalty, as a form of behaviroal intention (Gupta et al., 2018), commitment, more constant and long-term preference, setting customers more tolerant towards trivial alterations in the product/service (Bhattacharya and Sen, 2003), and accepting and utilizing modern technologies (Hao, 2021). Identification rationalizes the motives that inspire individuals to associate to the organization, and fostering similarities with its members and differences with non-members (Martínez and Del Bosque, 2013). Prior research has supported the association between identification and trust (So, et al., 2013; Rather, 2018). Other studies also indicated the positive impact of identification on AI benefits through improving their perceptions of service quality, perceived value, satisfaction and brand trust (So et al., 2013). Besides, identification's intervention positive role on customer trust has been reported by Martínez and Del Bosque (2013). Therefore, customers who positively identify themselves with a particular hotel are most likely to build trust and promote a better perception of gained AI benefits. Based on this, the moderating role of identification is predicted, proposing the following hypotheses:

H11a: Identification positively and significantly moderates the impact of AI-importance on customer trust.
H11b: Identification positively and significantly moderates the impact of AI-importance on AI benefits.

The moderating effect of perceived ease of use

Perceived Ease of Use (hence, easiness, representing UTAUT2's "Facilitating Conditions") is defined as "the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989). Frequently, models and theories integrated easiness as an antecedent of acceptance of technology, perceived usefulness, and intention to be adopted, since the easier it is to utilize technology, it is perceived as being more useful (Venkatesh, 2000). Thus, in order to properly adopt digitalization, it is imperative to comprehend the leading provision for easiness, as an essential moderating step towards developing and maintaining customers' acceptance and due adoption (Wu et al., 2021). The literature frequently supported the positive effect of easiness on AI-benefits in hospitality (De Kervenoael et al., 2020). Hao (2021) and Chen et al. (2022) stated that facilitating conditions are a major antecedent of accepting and adopting novel technologies. The literature also provided support for the relationship between easiness and trust (Agag and El-Masry, 2016). For example, Pai et al. (2018) confirmed that the easiness of biometric technology positively affected visitors' perceptions of trust. Consequently, customers who perceive a certain technological application as easy to use have the most potential to perceive it as more beneficial, and trust the organization providing it. Thus, the moderating role of easiness is predicted, proposing the following hypotheses:

H12a: Easiness positively and significantly moderates the impact of AI-importance on customer trust.
H12b: Easiness positively and significantly moderates the impact of AI-importance on AI-benefits. 1

Methods

Questionnaire development and pre-testing

This study is an exploratory and empirical one that adopted a quantitative approach by using a survey questionnaire. Before commencing data gathering, a pre-test was carried out with seven expert academics and 16 frequent hotel customers. Based on their responses, a few minor changes were addressed to enhance the questionnaire content validity.

Respondents were asked to participate in the survey only if they had patronized 3-, 4-, or 5-star hotels in the previous 6 months. Since the travel and vacation industry's activities almost ceased due to the pandemic, it was impossible to approach actual hotel customers to survey respondents. Rather, the preliminary question aimed at guaranteeing that respondents had experienced recent hotel accommodation and relevant hospitality services, to better assess the AI-importance in hotels, including how much the respondents would trust AI-adopting hotels and what their behavioral intentions would be.

The questionnaire includes three main sections. In the first one, AI importance as a multi-dimensional construct was measured through three main dimensions; namely, the biometrics (eight statements adopted from Murphy and Rottet, 2009), robotics (eight statements adopted from Ivanov et al., 2017), and self-service technologies (nine statements adopted from Ivanov et al., 2017*)*. AI importance was operationalized as higher-order factors. These dimensions were gauged by using a 5-point Likert scale, where 1 = not important at all and 5 = very important. Another section of the questionnaire was assessing; AI benefits in hotels (four statements adopted from Lu, 2019), trust (four statements adopted from Martínez and Del Bosque, 2013) and their behaviroal intentions towards hotels adopting AI (four statements adopted from Kim, et al., 2009). A third area of questions focused on evaluating the personal-service (four statements adopted from Beatson, 2010), reputation (four statements adopted from Jalilvand et al., 2017), easiness (three statements adopted from Venkatesh, 2000), and identification (four statements adopted from Martínez and Del Bosque, 2013). By using a 5-point Likert scale, the survey questions were formulated, where 1 = strongly disagree and 5 = strongly agree. The questionnaire ended with some demographic questions.

Population and sample

Respondents were preliminarily asked to participate in the survey only if they had patronized 3-, 4-, or 5-star hotels in the previous 6 months. This opening question aimed at guaranteeing that respondents had experienced recent hotel accommodation and relevant hospitality services, to better assess the variables of the study.

A sample frame for the population was unknown, therefore a non-probability sampling approach was selected, whereby a two-stage sampling process has been employed: firstly, *the convenience sampling* and then *the snowball techniques*. Convenience sampling was applied to reach 'convenient' sources of respondents (San Martín and Herrero, 2012) from several regions around the world. When the population is large, convenient sampling is successful (Etikan, et al., 2016), as in this study. In addition, it provides strong data when participation is high (Coviello and Jones, 2004). It is also the frequently selected sampling technique in hospitality studies due to the impossibility of accessing all available electronic sources of hotel customers around the world.

As mentioned before, and due to the surge of COVID-19, it was not possible to approach actual hotel guests. Due to this dilemma, the authors had to choose between a statistically valid sample of the most accessible part of the target population, which will be absolutely limited, and a statistically less-valid and less-representable sample of broader coverage. That is why we resorted to snowball sampling, which is used when characteristics to be possessed by samples are rare and/or difficult to find, and where a population is hard to locate and tough to choose subjects to assemble them as samples for research. Snowball sampling may also help discover characteristics about usually inaccessible populations. And to avoid the common bias of snowball sampling, respondent-driven sampling was, in part, implemented. The authors could not be able to determine the tally of respondents recruited by each study subject initially contacted. Still, initial study subjects were asked to select from among their acquaintances, their own peers. This approach would mostly assure minimum level of homophily and homogeneity on attributes in the population.

The questionnaire was designed using Google Forms. Respondents were contacted through a number of hotel chains, that distributed the e-form questionnaire through their websites and customer databases. Second, a snowball sampling technique was utilized to collect data from respondents through an online survey. Because of its relevant restrictions, the online survey was shared with conceivable participants within professional and social networks (e.g., WhatsApp, and Linked-In), which they then shared with their networks (Salem et al., 2021, 2022, 2023; Ghazi, 2018; Ghazi and Ammar, 2018; Ghazi, et al., 2023).

The typical sample size for Structural Equation Modeling (SEM) is approximately 200 cases. However, more than 400 cases are adequate for examining a theoretical inclusive model (Kline, 2011). The responses obtained were from 451 previous hotel clients, of which 416 were valid. From the total usable sample (416), 60.8% of the respondents were men and 39.2% were women. Respondents represented diverse age groups; 36.1% were from 28 to 37, 29.3% were from 38 to 47, 18.8% were from 18 to 27, 12.3% were from 48 to 57, and 3.6% were from 58 years old and above. Most of the respondents were master's degree holders (54.1%), followed by those with university education (22.8%), then Ph.D. holders (19.7%), and finally those with secondary education (3.4%). Respondents were from different geographic areas; about 31% were from the MENA region, 27.6% were from Europe and North America, 24% were from Asia, and 17.3% were from Africa.

Data analysis and results

Data analysis

Partial Least Squares-Structural Equation Modeling (PLS-SEM) was used by exploiting WarpPLS7 (Kock, 2020). Prior to testing the model, normality, multicollinearity and common method bias (CMB) tests were carried out by using the average full collinearity variance inflation factor (AFVIF) that affirmed all variables had values of less than 3.00, which is ideal (Kock, 2020). The PLS-SEM assessment comprised of a two-step process; the measurement model through confirmatory factor analysis (CFA), followed by testing the hypothesized structural relationships among the key constructs included in the conceptual model (Hair et al., 2017).

Measurement model

In this research, the guidelines of Hair et al. (2017) have been followed, recommending the selection of reflective constructs. We first assessed the convergent validity which includes the composite reliability (CR), Cronbach's Alpha, average variance extracted (AVE), and the variance inflation factor (VIF). Table 1 displays the value of the CR and Cronbach Alpha values, which exceeded the appropriate level of 0.7. AVE values were higher than the value of 0.5 (range, 0.584–0.811), which intimates an adequate convergent validity (Fornell and Larcker, 1981). Moreover, all variables had VIF values of below 3.3 (range 1.142–3.126),

Table 1. Convergent validity.

Variable	Composite reliability	Cronbach's alpha	AVE	VIF
Biometric authentication	0.926	0.908	0.613	2.016
Robotic process automation	0.918	0.898	0.584	2.404
Self-serve technologies	0.960	0.955	0.668	1.979
Customer trust	0.917	0.877	0.734	1.586
Perceived benefits	0.927	0.895	0.761	1.931
Preference for personal service	0.945	0.922	0.811	1.142
Perceived corporate reputation	0.924	0.890	0.751	2.270
Perceived ease of use	0.921	0.884	0.744	1.518
Customer-company-identification	0.908	0.864	0.713	3.126
Behavioral intention	0.931	0.901	0.771	2.281

Note. AVE = average variance extracted; VIF = variance inflation factor.

Table 2. Discriminant validity.

Constructs	1	2	3	4	5	6	7	8	9	10
Squared roots of average variance extracted (AVE)										
1. Biometric authentication	**0.783**	—	—	—	—	—	—	—	—	—
2. Robotic process automation	0.637	**0.764**	—	—	—	—	—	—	—	—
3. Self-serve technologies	0.566	0.652	**0.817**	—	—	—	—	—	—	—
4. Customer trust	0.300	0.202	0.174	**0.857**	—	—	—	—	—	—
5. Perceived benefits	0.376	0.439	0.412	0.429	**0.872**	—	—	—	—	—
6. Preference for personal service	0.209	0.107	0.031	0.224	0.071	**0.900**	—	—	—	—
7. Perceived corporate reputation	0.390	0.359	0.346	0.507	0.586	0.033	**0.867**	—	—	—
8. Perceived ease of use	0.300	0.357	0.309	0.366	0.513	0.119	0.444	**0.862**	—	—
9. Customer-company-identification	0.413	0.403	0.284	0.402	0.471	0.122	0.569	0.421	**0.844**	—
10. Behavioral intention	0.412	0.510	0.440	0.452	0.537	−0.007	0.637	0.448	0.557	**0.878**
Heterotrait-monotrait HTMT										
1. Biometric authentication	—	—	—	—	—	—	—	—	—	—
2. Robotic process automation	0.708	—	—	—	—	—	—	—	—	—
3. Self-serve technologies	0.609	0.705	—	—	—	—	—	—	—	—
4. Customer trust	0.335	0.228	0.192	—	—	—	—	—	—	—
5. Perceived benefits	0.419	0.490	0.446	0.484	—	—	—	—	—	—
6. Preference for personal service	0.228	0.157	0.084	0.249	0.079	—	—	—	—	—
7. Perceived corporate reputation	0.433	0.403	0.376	0.575	0.656	0.059	—	—	—	—
8. Perceived ease of use	0.330	0.401	0.337	0.415	0.574	0.133	0.500	—	—	—
9. Customer-company-identification	0.471	0.403	0.314	0.458	0.537	0.139	0.649	0.482	—	—
10. Behavioral intention	0.457	0.567	0.476	0.511	0.598	0.048	0.712	0.501	0.631	—

HTMT ratios (good if <0.90, best if <0.85).

which is perfect, in addition to the lack of both multicollinearity and common method bias (Kock, 2020). CFA is shown in Appendix A.

Secondly, as shown in Table 2, the square root of AVE for each construct with correlations among the latent variables was examined, revealing an acceptable discriminant validity (Fornell and Larcker, 1981). Additionally, Henseler et al. (2015) introduced an alternative and novel method to verify discriminant validity that concentrates on the multitrait-multimethod matrix to assess discriminant validity; the heterotrait-monotrait (HTMT) ratio of correlations (see Table 2). To meet the HTMT criterion, each value must be equal to or below 0.85. All study variables have values less than 0.85, showing that discriminant validity was satisfactory.

Structural model and hypotheses testing

The structural model was estimated using goodness-of-fit indices, standardized path coefficients (β-value), significance level (t statistic), effect sizes (f^2), and R^2 estimates (Hair et al., 2017). To estimate the model fit, standardized root mean square residual (SRMR) was employed (Henseler et al., 2015). An SRMR value of 0 would indicate an ideal fit, and generally, an SRMR value of ≤0.1 is rated as satisfactory for PLS models (Kock, 2020). In this study, an SRMR of 0.065 resulted in a satisfactory model fit.

As shown in Table 3, all hypothesized relationships were supported, except for H9a *(*AI importance - > *Personal-service - > trust: β-value = -0.068, and t value = -1.395)*, H11a *(*AI importance - > *CCI- > trust: β-value = 0.052 and t value = 0.822)*, H11b *(*AI importance *- > CCI - > AI benefits: β-value = 0.040 and t value = 0.809)*, and H12a *(*AI importance - > *Easiness > trust: β-value = 0.039 and t value = 0.806)*. Furthermore, R^2 values below 0.25 show a weak accuracy, those lower than 0.50 indicate a moderate accuracy, and values below 0.75 imply a solid predictive accuracy. AI importance during the COVID-19 pandemic explained 41% of the variance in behavioral intentions ($R^2 = 0.41$). The R^2 value of 41% is greater than the 0.25, implying a noteworthy model. Moreover, the effect size (f^2) exhibits whether the effects stipulated by path coefficients are small, medium, or large. Kock (2020) clarified that the values commonly implied are 0.02, 0.15, and 0.35, sequentially. As shown in Table 3, most relationships had a medium effect.

Table 3. Hypotheses-testing summary.

No.	Hypotheses	Beta	*p*-*Value*	*t*	Supported?	f^2
H1	AI-importance has a positive influence on customers' BIs	0.421	<0.001	9.1**	Yes	0.215
H2	AI-importance has a positive influence on customer trust	0.276	<0.001	5.8**	Yes	0.075
H3	AI-importance has a positive influence on AI-benefits	0.475	<0.001	10.3**	Yes	0.226
H4	AI-benefits have a positive on customer trust	0.352	<0.001	8.5**	Yes	0.172
H5	Trust has a positive influence on BIs	0.369	<0.001	7.9**	Yes	0.161
H6	AI-benefits have a positive influence on BIs	0.409	<0.001	8.1**	Yes	0.292
H7a	AI-benefits positively mediate AI-importance and trust	0.188	<0.001	1.7*	Yes	0.052
H7b	AI-benefits positively mediate AI-importance and BIs	0.179	<0.001	7.5**	Yes	0.095
H8a	Customer trust positively mediates AI-importance and BI	0.102	0.002	9.2**	Yes	0.054
H8b	Customer trust positively mediates AI-benefits and BIs	0.141	<0.001	8.8**	Yes	0.077
H9a	Personal-service positively moderates AI-importance and customer trust	−0.068	0.082	−1.395	No	0.023
H9b	Personal-service positively moderates AI-importance and AI-benefits	−0.217	<0.001	−4.6**	Yes	0.023
H10a	Reputation positively moderates AI-importance and customer trust	0.110*	0.021	2.285**	Yes	0.025
H10b	Reputation positively moderates AI-importance and AI-benefits	0.252	<0.001	5.317**	Yes	0.111
H11a	Identification positively moderates AI-importance and customer trust	0.052	0.223	0.822	No	0.019
H11b	Identification positively moderates AI importance and AI-benefits	0.040	0.206	0.809	No	0.009
H12a	Easiness positively moderates AI-importance and trust	0.039	0.210	0.806	No	0.019
H12b	Easiness positively moderates AI-importance and AI-benefits	0.190	<0.001	3.975**	Yes	0.078

***t* value for two-tailed tests: 1.960 ($p < 0.001$), **t* value for one-tailed tests: 1.645 ($p < 0.01$).

Table 4. Summary of mediation results.

Paths	Significance		Confidence intervals			Mediation	
	Direct effect	Indirect effect	95% LL	95% UL	VAF	%	Outcome
AI-importance on customer trust via *AI benefits*	0.083*	0.188**	0.094	0.282	0.693	69.3	Partially mediated
AI-importance on BIs via *AI-benefits*	0.352**	0.179**	0.112	0.246	0.337	33.7	Partially mediated
AI-importance on BIs via *trust*	0.421**	0.102**	0.035	0.168	0.195	20	Partially mediated
AI-benefits and BIs via *trust*	0.409**	0.141**	0.075	0.208	0.256	25.6	Partially mediated

**$p < 0.01$; *$p < 0.05$; LL, Lower level; UL, Upper level; VAF, Variance Accounted For.

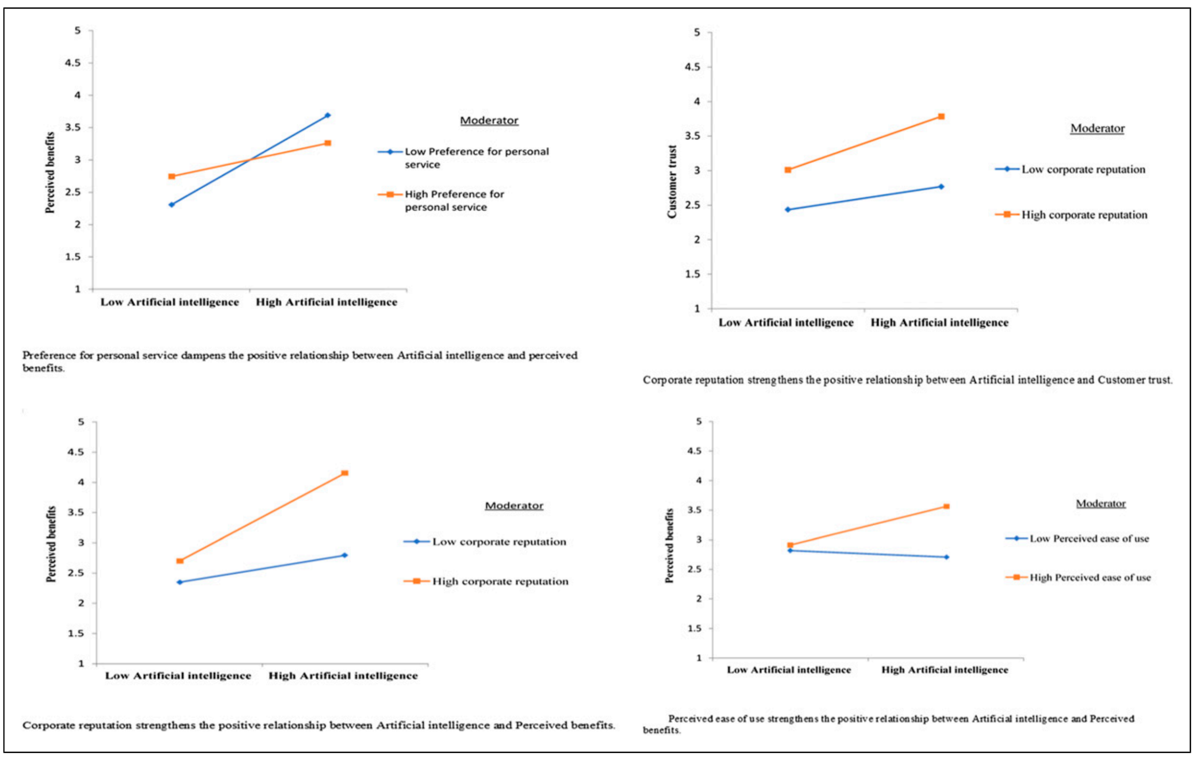

Figure 2. Moderation analysis.

Table 4 exhibits the ***mediation analysis*** results. The variance accounted for (VAF) confirms the indirect effect size and the total effect are connected. Values above 80% exemplify full mediation, those within 20% and 80% imply partial mediation, and values below 20% reveal no mediation force (Zhao et al., 2010). Table 4 exhibits that all mediating effects are partially supported.

The ***moderation effects*** by using the two-stage approach were also measured. The formula proposed by Kock (2020) was used to evaluate the variations in path coefficients between AI importance and both AI benefits and trust models. The t-statistics were determined and are exhibited in Table 3. The projected standardized path coefficients for the effect of the moderator on AI benefits ($\beta = -0.217$; $p < 0.001$) were significant (see Table 3). Therefore, personal-service dampens the positive association between AI-importance and AI-benefits (see Figure 2). Likewise, as shown in Table 3 and Figure 2, reputation strengthens the positive relationship between AI importance, trust and AI benefits, while easiness increases the positive relationship between AI importance and AI benefits. As explained earlier, H9a, H11a, H11b, and H12a were not supported, as no moderation effects were experienced.

Conclusions and implications

Conclusions

As a result of the pandemic, potential hotel customers are more concerned with utilitarian, concrete benefits and outcomes than with emotional perspectives such as trust. Likewise, triggered by the pandemic, customers are also more compelled by tangible influencing variables, such as preference for personal service, and ease of use, than social influences, such as corporate reputation and identification with the company. It was confirmed that the higher the potential guests' perceived AI-importance, the higher their behavioral intentions towards AI-applying hotels will be during and post-COVID-19. This conforms to previous studies (e.g., Shin and Kang, 2020; Zhong et al., 2020), confirming that customers' behavioral intentions are positively influenced by their awareness of the value of novel technologies. This also corresponded to UTAUT2's assumption that performance expectancy has a significant effect on attitudes and intentions to use various innovative technologies (Hao, 2021; Jung and Cha, 2022; Morosan and DeFranco, 2016; Wu et al., 2021).

This urging need for tangible value was apparent in that the AI-benefits are more influential across various investigated correlations than trust, either as a direct predictor, a dependent variable, or as an efficacious mediator. This implies that the pursuit of solid gains by potential guests surpasses and precedes their need for trust. The results indicate that the more potential customers perceive AI as being important, the more this would build their trust in AI-adopting hotels, which conforms with Tussyadiah et al. (2020) and Ruan et al. (2020). Furthermore, Wu et al. (2021) confirmed that AI-importance has a more significant effect on AI-benefits. This result proves that the current study's variation of UTAUT2 is significant, whereby performance expectancy significantly and positively impacts effort expectancy.

Besides, it was proved that AI-benefits have a substantial effect on trust. This conforms to prior studies, which revealed that AI-benefits positively influenced trust, in addition to mediating the impact of AI-importance on trust (Ameen et al., 2021; Lee and Lee, 2019; Ruan et al., 2020).

In addition, it was supported that trust has a significant effect on BI, a result that was also supported through previous studies (Tussyadiah et al., 2020; Ruan et al., 2020; Wu et al., 2021). Nevertheless, results once again assert the worth of AI-benefits for customers, where it is found to have a significant effect on behavioral intentions. An added argument that verifies the fundamental role of AI benefits is that results show that AI-benefits play a partial mediating role through the impact of AI importance on trust. This implies that even trust, as a common key variable, is also preceded and foreshadowed by AI-benefits. This agrees with studies proving that various forms of AI-benefits mediate the impact of AI-importance on trust (Ameen et al., 2021; Pinxteren et al., 2019; Ruan et al., 2020). The findings also revealed that the correlation between AI-importance and behavioral intentions is partially mediated by AI-benefits, to a greater extent than trust. These results validate the investigation and the inclusion of the customers' utilitarian versus emotional perceptions into UTAUT2.

Furthermore, results confirmed the necessity of gaining trust, which significantly mediates the relationship between AI-benefits and behavioral intentions. A rather insubstantial mediating magnitude assures the previously induced inference that customers now seek more tangible outcomes. Customer trust was found to play a mediating role between AI-importance and AI-benefits (Ameen et al., 2021; Ruan et al., 2020) and between AI-benefits and behavioral intentions (Wang et al., 2015; Lee and Lee, 2019). This strongly suggests that AI-benefits play a critical role in the decision-making process of supporting and dealing with AI-adopting hotels. These findings are consistent with previous research (Davis, 1989; De Kervenoael et al., 2020; Lin et al., 2020) indicating that perceived AI-benefits, value, and usefulness have a direct impact on customers' intentions and positive emotions to support and use new technologies. AI-benefits have also been shown to play a mediating role in the relationship between AI-importance and behavioral intentions (Pinxteren et al., 2019; Ruan et al., 2020).

Results additionally indicated that personal service is not moderating the relationship between AI-importance and trust. A logical inference is that personal-service, as a moderator, dampened the relationship between AI-importance and AI-benefits. This sheds light on the fact that, in spite of the pandemic and its compelling impacts on the hospitality industry, and despite the tendency towards recent technological applications and solutions, the human touch is still much appreciated in the hospitality industry, and it will deter the full automation of service processes. This coincides with previous empirical studies that proved the negative association between personal-service and AI-benefits of technology (Shin and Kang, 2020; Ameen et al., 2021).

The fact that tangible values are preferred to the indirectly rewarding, emotional aspects is also perceptible in other moderating relationships. The rather concrete variable "reputation," which typically necessitates the formulation of a solid foundation (Walsh et al., 2009), moderates the relationship between AI-importance and both AI-benefits and trust. Furthermore, the effect of reputation, similar to UTAUT2's "Social Influence," is more significant when it modifies the relationship between AI-importance and AI-benefits rather than trust. This implies that the more reputable the hotel is, the more potential customers would perceive AI practices as being more beneficial and would subsequently trust the AI-adopting hotel. These findings are consistent with previous research indicating the importance of reputation in forming trust (Jalilvand et al., 2017; Chang, 2013) and influencing AI-benefits (Perez-Aranda et al., 2019; Chang, 2013).

The results also indicated that identification, which represents UTAUT2's "social influence", which is a rather sentimental and intangible construct, does not moderate the relationships between AI-importance and trust nor between AI-importance and AI-benefits. This finding contradicts previous research that suggested the AI-importance of identification in achieving AI benefits (So et al., 2013; Rather, 2018). This disagreement can be attributed to COVID-19 circumstances, which engender different perceptions and varied responses to variables than those commonly established, and which push customers towards the pursuit of more tangible outcomes. Moreover, the results confirmed that ease, representing UTAUT2's "facilitating conditions," does not moderate its relationship with trust. This contradicts existing literature that supports the impact of ease on trust building (Agag and El-Masry, 2016; Chen et al., 2022; Hao, 2021; Pai et al., 2018). This might also be due to the same rationale: COVID-19 has directed potential customers' interests towards more functionality and pursuing material outcomes. Meanwhile, the results confirmed previous research that ease, as a utilitarian perception (Davis, 1989), moderates the impact of AI-importance on its benefits (De Kervenoael et al., 2020).

Theoretical implications

This study presents a novel perception of how to integrate trendy operational solutions to deal with and recover from a crisis. In addition, it incorporates customer-decision-related utilitarian and emotional variables in the proposed model, which provides a workable extension to UTAUT2. AI solutions have been integrated with key moderating and mediating variables, with the ultimate goal of configuring how to build positive behavioral intentions towards AI-adopting hotels during COVID-19, and in similar crises.

This study complements the empirical research gap concerning utilizing AI applications for amid and post-pandemic management (Ivanov et al., 2020; Seyitoğlu and Ivanov 2020; Shin and Kang, 2020), utilizing UTAUT2 to frame and streamline the study findings. Additionally, the current study examined AI-importance, AI-benefits, trust, identification, reputation, personal-service, and easiness variables, to provide a holistic, generalizable model that fits in most operational settings to positively steer customers' behavioral intentions towards the hotel's best interests, to make up for relevant shortages spotted in previous studies (Ruan et al., 2020; Shin and Kang, 2020; Tussyadiah, 2020; Zhong et al., 2020).

Another apparent, statistically validated implication is the study's applicable extension to UTAUT2's to a broader spectrum through exchanging the traditional UTAUT2's variables. This aimed at specifically incorporating a vast array of hypothesized correlations that would most fit into the operational status quo of hotels during and post COVID-19 and similar crises. Furthermore, other research-related outcomes are augmenting UTAUT2's framework by additional, parallel variables to broaden the applicability of UTAUT2, and ultimately inspiring researchers to utilize the UTAUT2 as a launching point towards more exploratory studies according to concurrent needs of the hospitality industry.

Managerial implications

The current study posits several practical implications for involved stakeholders, particularly hotel managers. The major implication is expressed by Gaur et al. (2021), who urged hospitality practitioners to foster available knowledge to recover the COVID-19 crisis via resorting to digitalization solutions, with AI on top of technological innovations, not only for the sake of recovery, but also for thriving business and re-developing guests' interest. Particularly, the extended UTAUT2 model examined is provided for effective managerial implications to institute the proper and purposeful adoption of AI technologies, and to survive and recover from the pandemic, by developing and sustaining customers' interest and trust during and post COVID-19, and in similar crises.

First and foremost, managers should exploit and make best use their customers' pursuit of material, tangible gains; a need that is driven by fear from contagion and by the desire to obtain required services and products seamlessly. Thus, rather than just jacking a trend, hoteliers should steer their implementation of AI towards specific operational objectives that fulfil customers' concurrent, COVID-19-driven expectations and needs, comprising cognitive and social benefits, value, convenience, practicality, quality, reliability, user-friendliness, security, and privacy. All those notions need to be supported by hotel managers to obtain the full potential of AI solutions.

Second, customer trust is an important determinant among AI-related variables, and the eventual behavioral intentions. Hoteliers should develop and maintain their customers' health-related and operational trust through providing AI applications that are easy to use, dependable, effective, time and cost-efficient, and, above all, guarantee the proper social distancing that does not deter smooth operations. Thus, trust should be provoked by linking it to material benefits to best appeal for customers, rather than just being an emotional prospect that might not matter to customers in times of crises. Hence, hotels would associate and gain both cognitive and emotional support from customers, eventually leading to positive behavioral intentions.

Third, it is also imperative that managers, besides maximizing benefits, and supporting trustworthiness, should take due measures to stabilize and enhance their corporate reputation. This is attainable throughout monitoring and measuring customers' reaction to and evaluation of the hotel's goods, services, communication activities, interactions with the company and/or its representatives (Walsh, et al., 2009), and enhancing the corporate transparency, assuming social responsibility, pursuing business ethics, and preventing unfair competition (Almeida and Coelho, 2019). Furthermore, the corporate reputation should be portrayed as providing AI-assisted operations for the best interests of customers, their crisis-related concerns, and their pursuit for more facilitated, yet personalized, services.

Fourth, It is not only compelling to adopt and implement AI; but it is also crucial that managers devise workable, feasible measures to periodically track and assess customers' behavioral intentions as a rational, eventual outcome.

Fifth, it was advised by several respondents that AI can be applied in functions that already involve a tangible product, like food and beverage outlets and housekeeping tasks. However, where functions are purely service centered, like reservations, check-in and check-out, it is preferred for them to be administered through human contact, where AI should only be integrated to enhance the service experience, not to substitute the human-based hospitable service encounters. That is, AI should be advertised as a means of facilitating and enriching customers' service experience, thus enabling the "human and personal" hospitality element to be enhanced towards more personalized service, rather than advertising AI as a tool for decreasing personal contact, that would otherwise resent customers.

Since perceived "Customer-Company Identification" is associated with the company's trustworthiness, thus, customers' inclination towards such an identification, as an emotional construct, will not be substantial during crises. Consequently, identification should be elicited and incited through including AI-assisted service capacities. AI usage should not then be solely a means of enhancing services and product delivery, rather, AI should be directed as a utility towards soliciting customers' needs and wants, and incorporating them into designing and creating personalized packages, services, and communications. Accordingly, customers will not perceive identification as an ineffectual element in forming their behaviroal intentions towards AL-adopting hotels. Rather, identification will be appreciated as being associated with quantifiable, pertinent outcome, particularly during and after crises.

Moreover, hotel managers have to carefully monitor data privacy and security issues, since some respondents welcomed using AI applications, but were hesitant to use biometric identification to pay their bills, while others were totally against biometric identification. Thus, hotels should provide their guests with multiple options for these concerns. In addition to the indispensable security concerns, to influence behavioral intentions further positively, it is essential for hospitality managers and practitioners to boost their AI applications' perceived usefulness, ease of use, interactivity, responsiveness, and innovativeness. Finally, those AI-inherent features must not come on the account of anthropomorphism, so as not to miss the hospitality-inbuilt human touch and the personalized flair. Ultimately then, customers will build up and effectuate their proclivity to use AI applications.

Since COVID-19 is almost done, it is rather essential to comprehend that those implications are equally essential and applicable to stimulate customers' behavioral intentions during and amid other types of crises, and to minimize or compromise the effect of other types of turmoil. AI applications' versatility directly supports the aspects that are usually most adversely affected, improving service quality, increasing operational capability and efficiency, lowering costs, and consequently creating a competitive advantage for AI-adopting hotels during crises. AI-contactless solutions help recover customer trust and encourage demand through keeping social and physical distance and lowering costs, which are the major customers' concerns during health and economic risks.

Limitations and future directions

The current study was directed towards customers of hotels. Further studies are needed to examine the proposed model in other tourism and hospitality sectors and in specific geographical areas, discerning the needs of various types of customers.

Furthermore, this study focused only on the positive aspects and AI-benefits during the pandemic. Future research should investigate the negative aspects and drawbacks of AI, and whether they would hinder customers from accepting AI in response to the threats posed by COVID-19.

Further research should investigate how each type of AI fits individually into the proposed model, rather than biometric authentication, robotics, and self-serve technologies. Moreover, more concern have to be directed to the utilization of Metaverse and ChatGPT, and their role towards minimizing crisis-related operational drawbacks.

Rather than just surveying customers, a natural extension of the current study is to scrutinize AI and its applications during crises from an organizational and strategic perspectives by surveying hotel chains' trendsetters and regional directors, tourism and hospitality establishment owners, managers, supervisors, and employees.

To gain more insights into how customers process their decisions, a qualitative, rather than quantitative, methodology should be utilized to acquire deeper acumen on how customers proceed through each phase of the guest cycle, starting from planning their trip, and extending through their post-service preferences.

Finally, researchers and theorists should be encouraged to launch novel, augmented versions from UTAUT2 to specifically suit and investigate recent, urging technology-related operational needs and research gaps, and extend UTAUT2's viability to more spectrums.

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References

Agag G and El-Masry A (2016) Why do customers trust online travel websites? Drivers and outcomes of customer trust toward online travel websites. *Journal of Travel Research* 56(3): 347–369.

Ajzen I (1991) The theory of planned behavior. *Organizational Behavior and Human Decision Processes* 50(2): 179–211.

Almeida M and Coelho A (2019) The antecedents of corporate reputation and image and their impacts on employee commitment and performance: The moderating role of CSR. *Corporate Reputation Review* 22(1): 10–25.

Ameen N, Tarhini A, Reppel A, et al. (2021) Customer experiences in the age of artificial intelligence. *Computers in Human Behavior* 114: 106548.

Beatson A (2010) Self-service technology and the moderating effects of consumer characteristics. *International Journal of Services Technology and Management* 14(2/3): 278–302.

Bhattacharya CB and Sen S (2003) Consumer–company identification: A framework for understanding consumers' relationships with companies. *Journal of Marketing* 67(2): 76–88.

Cha SS (2020) Customers' intention to use robot-serviced restaurants in Korea: relationship of coolness and MCI factors. *International Journal of Contemporary Hospitality Management* 32(9): 2947–2968.

Chang KC (2013) How reputation creates loyalty in the restaurant sector. *International Journal of Contemporary Hospitality Management* 25(4): 536–557.

Chen C, Chen H and Wang Y (2022) Cash, credit card, or mobile? Examining customer payment preferences at chain restaurants in Taiwan. *Journal of Foodservice Business Research* 25(2): 148–167.

Coviello NE and Jones MV (2004) Methodological issues in international entrepreneurship research. *Journal of Business Venturing* 19(4): 485–508.

Dabholkar PA and Bagozzi RP (2002) An attitudinal model of technology-based self-service: moderating effects of consumer traits and situational factors. *Journal of the Academy of Marketing Science* 30(3): 184–201.

Dardeer M, Tag-Eldeen A and Salem I (2017) The influence of physical work environment on hotel back-of-the-house employees' satisfaction and productivity: A Case Study on Hilton Hotels. *Journal of Tourism Research* 5(18): 45–64.

Davis FD (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13(3): 319–340.

de Kervenoael R, Hasan R, Schwob A, et al. (2020) Leveraging human-robot interaction in hospitality services: Incorporating the role of perceived value, empathy, and information sharing into visitors' intentions to use social robots. *Tourism Management* 78: 104042.

Elkhwesky Z, El Manzani Y and Elbayoumi Salem I (2022) Driving hospitality and tourism to foster sustainable innovation: A systematic review of COVID-19-related studies and practical implications in the digital era. *Tourism and Hospitality Research*.

Etikan I, Musa S and Alkassim R (2016) Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics* 5(1): 1–4.

Fishbein M and Ajzen I (1977) Belief, attitude, intention, and behavior: An introduction to theory and research. *Philosophy and Rhetoric* 10(2): 177–188.

Fornell C and Larcker DF (1981) Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research* 18: 39–50.

Gaur L, Afaq A, Singh G, et al. (2021) Role of artificial intelligence and robotics to foster the touchless travel during a pandemic: a review and research agenda. *International Journal of Contemporary Hospitality Management* 33(11): 4079–4098.

Gursoy D and Chi CG (2020) Effects of COVID-19 pandemic on hospitality industry: review of the current situations and a research agenda. *Journal of Hospitality Marketing and Management* 29(5): 527–529.

Gupta A, Dogra N and George B (2018) What determines tourist adoption of smartphone apps? An analysis based on the UTAUT-2 framework. *Journal of Hospitality and Tourism Technology* 9(1): 50–64.

Ghazi KM (2018) Hotel marketing deception practices and its effect on Guests' image. *Journal of Tourism Research* 20, 88–108.

Ghazi K and Ammar S (2018) International tourists' attitudes and satisfaction toward airport F&B, and duty-free concessions. *Journal of Tourism Research* 20, 41–109.

Ghazi KM, El-Said O, Salem IE and Smith M (2023) Does performance appraisal legitimacy predict employee sabotage and innovative behaviors? The mediating role of performance appraisal satisfaction. *Tourism Management Perspectives* 47, 101117.

Hair Jr JF, Matthews LM, Matthews RL, et al. (2017) PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis* 1(2): 107–123.

Hao F (2021) Acceptance of contactless technology in the hospitality industry: extending the unified theory of acceptance and use of technology 2. *Asia Pacific Journal of Tourism Research* 26(12): 1386–1401.

Hao F, Xiao Q and Chon K (2020) COVID-19 and China's hotel industry: Impacts, a disaster management framework, and post-pandemic agenda. *International Journal of Hospitality Management* 90, 102636.

Henseler J, Ringle CM and Sarstedt M (2015) A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science* 43(1): 115–135.

Ivanov S, Webster C and Berezina K (2017) Adoption of robots and service automation by tourism and hospitality companies. *Revista Turismo & Desenvolvimento* 27(28): 1501–1517.

Ivanov S, Webster C, Stoilova E, et al. (2020). Biosecurity, automation technologies and economic resilience of travel, tourism and hospitality companies. 1–34.þ

Jalilvand M, Nasrolahi Vosta L, Kazemi Mahyari H, et al. (2017) Social responsibility influence on customer trust in hotels: mediating effects of reputation and word-of-mouth. *Tourism Review* 72(1): 1–14.

Jung S, Shin YC, Oh KS, et al. (2022) Perceived control and work-related stress mediate the effects of grit on depression among employees. *Brain Sciences* 13(1): 9–16.

Kim J, Montes AA and Han H (2021) The role of expected benefits towards smart hotels in shaping customer behavior: comparison by age and gender. *Sustainability* 13(4): 1698.

Kim T, Kim WG and Kim HB (2009) The effects of perceived justice on recovery satisfaction, trust, word-of-mouth, and revisit intention in upscale hotels. *Tourism Management* 30(1): 51–62.

Kline RB (2011) *Convergence of structural equation modeling and multilevel modeling*.

Knani M, Echchakoui S and Ladhari R (2022) Artificial intelligence in tourism and hospitality: Bibliometric analysis and research agenda. *International Journal of Hospitality Management* 107: 103317.

Kock N (2020) *WarpPLS User Manual: Version 7.0*. Laredo, TX, USA: ScriptWarp Systems.

Lee SA and Lee J (2019) Enhancing customers' brand loyalty via branded hotel apps. *Journal of Quality Assurance in Hospitality & Tourism* 20(3): 339–361.

Li M, Yin D, Qiu H, et al. (2022) Examining the effects of AI contactless services on customer psychological safety, perceived value, and hospitality service quality during the COVID-19 pandemic. *Journal of Hospitality Marketing & Management* 31(1): 24–48.

Lin H, Chi OH and Gursoy D (2020) Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services. *Journal of Hospitality Marketing & Management* 29(5): 530–549.

Lu T (2019) *Opportunities of Artificial Intelligence in Hospitality Industry for Innovative Customer Services*. Doctoral Dissertation, Ho Chi Minh City, Vietnam.

Lukanova G and Ilieva G (2019) Robots, artificial intelligence, and service automation in hotels. *Robots, artificial intelligence, and service automation in travel, tourism and hospitality*. Emerald Publishing Limited.

Martínez P and Rodríguez del Bosque I (2013) CSR and customer loyalty: The roles of trust, customer identification with the company and satisfaction. *International Journal of Hospitality Management* 35: 89–99.

McKnight DH and Chervany NL (2001) What trust means in e-commerce customer relationships: An interdisciplinary conceptual typology. *International Journal of Electronic Commerce* 6(2): 35–59.

Morosan C and DeFranco A (2016) It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. *International Journal of Hospitality Management* 53: 17–29.

Murphy H and Rottet D (2009) An exploration of the key hotel processes implicated in biometric adoption. *International Journal of Contemporary Hospitality Management* 21(2): 201–212.

Pai CK, Wang TW, Chen SH, et al. (2018) Empirical study on Chinese tourists' perceived trust and intention to use biometric technology. *Asia Pacific Journal of Tourism Research* 23(9): 880–895.

Park S and Tussyadiah IP (2020) How guests develop trust in hosts: an investigation of trust formation in P2P accommodation. *Journal of Travel Research* 59(8): 1402–1412.

Perez-Aranda J, Vallespín M and Molinillo S (2019) Hotels' online reputation management: benefits perceived by managers. *International Journal of Contemporary Hospitality Management* 31(2): 615–632.

Perić M and Vitezić V (2021) Tourism getting back to life after COVID-19: Can artificial intelligence help? *Societies* 11(4): 115–213.

Pillai SG, Haldorai K, Seo WS, et al. (2021) COVID-19 and hospitality 5.0: Redefining hospitality operations. *International Journal of Hospitality Management* 94: 102869.

van Pinxteren MM, Wetzels R, Rüger J, et al. (2019) Trust in humanoid robots: Implications for services marketing. *Journal of Services Marketing* 33(4): 507–518.

Rather RA (2018) Investigating the impact of customer brand identification on hospitality brand loyalty: A social identity perspective. *Journal of Hospitality Marketing & Management* 27(5): 487–513.

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* 33(11): 4057–4078.

Ruan WQ, Zhang SN, Liu CH, et al. (2020) A new path for building hotel brand equity: The impacts of technological competence and service innovation implementation through perceived value and trust. *Journal of Hospitality Marketing & Management* 29(8): 911–933.

Salem IEB and Čavlek N (2016) Evaluation of hotel website contents: existence-importance analysis. *Journal of Hospitality and Tourism Technology* 7(4): 366–389.

Salem IE, Elbaz AM, Elkhwesky Z, et al. (2021) The COVID-19 pandemic: The mitigating role of government and hotel support of hotel employees in Egypt. *Tourism Management* 85: 104305.

Salem IE, Aideed H, Alkathiri NA and Ghazi KM (2022) Retaining talented employees during COVID-19 pandemic: The leverage of hotel pandemic response strategies. *Tourism and Hospitality Research*, 14673584221141294.

Salem IE, Abbas H, Mousa M, et al. (2023) Does dysfunctional customer behavior really impact the turnover intention of hotel guest-contact employees? The role of wisdom leadership and job embeddedness. *Journal of Hospitality Marketing & Management* 32(2): 150–173.

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

Saydam MB, Arici HE and Koseoglu MA (2022) How does the tourism and hospitality industry use artificial intelligence? A review of empirical studies and future research agenda. *Journal of Hospitality Marketing & Management* 31(8): 908–936.

Seyitoğlu F and Ivanov S (2020) A conceptual framework of the service delivery system design for hospitality firms in the (post-) viral world: The role of service robots. *International Journal of Hospitality Management* 91: 102661.

Shin H and Kang J (2020) Reducing perceived health risk to attract hotel customers in the COVID-19 pandemic era: Focused on technology innovation for social distancing and cleanliness. *International Journal of Hospitality Management* 91: 102664.

So KF, King C, Sparks BA, et al. (2013) The influence of customer brand identification on hotel brand evaluation and loyalty development. *International Journal of Hospitality Management* 34: 31–41.

Talwar S, Kaur P, Nunkoo R, et al. (2022) Digitalization and sustainability: Virtual reality tourism in a post pandemic world. *Journal of Sustainable Tourism*: 1–28.

Tussyadiah I (2020) A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism. *Annals of Tourism Research* 81: 102883.

Tussyadiah I, Zach F and Wang J (2020) Do travelers trust intelligent service robots? *Annals of Tourism Research* 81: 102886.

Venkatesh V (2000) Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research* 11(4): 342–365.

Venkatesh V, Thong J and Xu X (2012) Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly* 36(1): 157–178.

Walsh G, Mitchell V, Jackson P, et al. (2009) Examining the antecedents and consequences of corporate reputation:

A customer perspective. *British Journal of Management* 20(2): 187–203.
Wang L, Law R, Guillet B, et al. (2015) Impact of hotel website quality on online booking intentions: eTrust as a mediator. *International Journal of Hospitality Management* 47: 108–115. þ.
Wu R, Lee J and Tian X (2021) Determinants of the intention to use cross-border mobile payments in Korea among Chinese tourists: An integrated perspective of UTAUT2 with TTF and ITM. *Journal of Theoretical and Applied Electronic Commerce Research* 16(5): 1537–1556.
Zeng Z, Chen P and Lew A (2020) From high-touch to high-tech: COVID-19 drives robotics adoption. *Tourism Geographies* 22(3): 724–734.
Zhao X, Lynch JG Jr and Chen Q (2010) Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research* 37(2): 197–206.
Zhong L, Sun S, Law R, et al. (2020) Impact of robot hotel service on consumers' purchase intention: a control experiment. *Asia Pacific Journal of Tourism Research* 25(7): 780–798.

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Appendix

Appendix A: Confirmatory factor analysis PLS approach.

Construct/items	Mean	SE	Loadings	*p*-value	Confidence 2.5%	Intervals 97.5%
AI-biometric authentication *(BA)*	3.75	0.970	—	—	—	—
BA.1 Online booking of a hotel room	3.31	1.56	0.641	<0.001	0.553	0.729
BA.2 Check-in and check-out processes	3.84	1.19	0.829	<0.001	0.743	0.915
BA.3 Entering the guestroom	3.85	1.17	0.779	<0.001	0.693	0.866
BA.4 Operating in-room services and functions	3.80	1.25	0.833	<0.001	0.747	0.919
BA.5 Locking the guestroom upon the guest's exit	3.96	1.23	0.821	<0.001	0.735	0.907
BA.6 Processing inquiries, ordering and booking hotel's products and services	3.63	1.20	0.804	<0.001	0.717	0.890
BA.7 Identifying guests when accessing various outlets	3.66	1.20	0.825	<0.001	0.739	0.911
BA.8 Processing and confirming various payments	3.89	1.15	0.708	<0.001	0.620	0.795
AI-robotic process automation *(RPA)*	3.41	0.914	—	—	—	—
RPA.1 Front Desk robots performing check-in and check-out functions	3.17	1.03	0.686	<0.001	0.599	0.774
RPA.2 Porter robots for luggage transferring	3.36	1.23	0.770	<0.001	0.683	0.857
RPA.3 concierge robots	3.30	1.29	0.768	<0.001	0.681	0.855
RPA.4 Vacuum cleaning and disinfectant robots for housekeeping purposes	3.71	1.19	0.771	<0.001	0.684	0.857
RPA.5 In-room assistant robots	3.65	1.16	0.741	<0.001	0.654	0.828
RPA.6 Delivery robots	3.45	1.17	0.805	<0.001	0.719	0.891
RPA.7 Robot restaurant servers, bartenders, and baristas	3.02	1.28	0.770	<0.001	0.683	0.857
RPA.8 Robot-assisted bill-payment	3.56	1.19	0.794	<0.001	0.707	0.880
AI-self-serve technologies *(SST)*	3.57	0.971	—	—	—	—
SST.1 Self-service check in and check-out lobby kiosks	3.58	1.1956	0.799	<0.001	0.713	0.885
SST.2 Self-service mobile check in/out	3.71	1.1924	0.827	<0.001	0.741	0.913
SST.3 Self-service kiosks for information (concierges services)	3.51	1.1760	0.827	<0.001	0.741	0.913
SST.4 Ordering hotel's products and services using the hotel-specific mobile application	3.762	1.1443	0.823	<0.001	0.736	0.909
SST.5 Restaurant table-side ordering	3.630	1.1481	0.863	<0.001	0.778	0.949
SST.6 Restaurant table-side entertainment	3.233	1.2108	0.794	<0.001	0.708	0.881
SST.7 Restaurant table-side payment	3.740	1.1822	0.854	<0.001	0.768	0.940
SST.8 Conveyor/Roller-coaster restaurants	3.317	1.2303	0.821	<0.001	0.735	0.907
SST.9 Using glass cubbies	3.385	1.2128	0.833	<0.001	0.747	0.919
SST.10 Using chatbots	3.466	1.2530	0.802	<0.001	0.716	0.889
SST.11 Offering virtual Voice assistants in room standalone devices	3.577	1.1858	0.770	<0.001	0.683	0.857
SST.12 Using a mobile Native Languages translations	3.909	1.1349	0.792	<0.001	0.706	0.879
Preference for personal service *(PPS)*	4.00	0.916	—	—	—	—
PPS.1 Face-to-face contact in providing services makes the process enjoyable	4.147	0.9769	0.908	<0.001	0.823	0.993
PPS.2 I like interacting with the person who provides the service	4.024	1.0548	0.943	<0.001	0.858	1.027
PPS.3 I like making conversation with the person who is providing the service	3.978	0.9679	0.853	<0.001	0.767	0.939
PPS.4 I have a preference for dealing with contact staff in service settings	3.858	1.0717	0.896	<0.001	0.811	0.981

(continued)

(continued)

Construct/items	Mean	SE	Loadings	*p*-value	Confidence 2.5%	Intervals 97.5%
Perceived benefits (PB)	3.84	0.808	—	—	—	—
PB.1 The hotel artificial intelligence reduces my searching time to access the hotel products that I need	3.868	0.9180	0.880	<0.001	0.795	0.966
PB.2 The hotel artificial intelligence can provide me with the convenience of instantly accessing the hotel products that I need	3.875	0.8719	0.884	<0.001	0.798	0.969
PB.3 I think that using artificial intelligence in a hotel can offer me a wider range of hotel products	3.767	0.9699	0.830	<0.001	0.744	0.916
PB.4 Overall, I feel that the hotel artificial intelligence is beneficial to access the hotel products	3.837	0.9530	0.893	<0.001	0.808	0.979
Perceived ease of use *(PEU)*	3.72	0.817	—	—	—	—
PEU.1 Learning to deal with artificial intelligence in hotels would be easy for me	3.861	0.9390	0.838	<0.001	0.752	0.924
PEU.2 My interactions with artificial intelligence in hotels would be clear and understandable	3.764	0.9196	0.909	<0.001	0.824	0.994
PEU.3 My interactions with artificial intelligence in hotels would not require a lot of mental effort	3.546	1.0026	0.816	<0.001	0.729	0.902
PEU.4 Overall, I believe artificial intelligence is easy to use	3.714	0.9352	0.883	<0.001	0.798	0.969
Perceived customer-company-identification *(CCI)*	3.15	0.889	—	—	—	—
CCI.1 When someone criticizes hotels that provide AI, it feels like a personal insult	2.887	1.0818	0.827	<0.001	0.741	0.913
CCI.2 I am very interested in what others think about hotels that provide AI.	3.450	0.9755	0.768	<0.001	0.681	0.854
CCI.3 When someone compliments hotels that provide AI, then it feels like a personal compliment	3.207	1.0439	0.890	<0.001	0.805	0.976
CCI.4 When I talk about hotels that provide AI, I usually say "we" rather than "they"	3.059	1.1090	0.887	<0.001	0.801	0.972
Perceived corporate reputation *(PCR)*	3.72	0.822	—	—	—	—
PCR.1 Highly regarded	3.724	0.9304	0.853	<0.001	0.767	0.938
PCR.2 Successful	3.788	0.9511	0.884	<0.001	0.799	0.969
PCR3 Well-established	3.805	0.9483	0.873	<0.001	0.787	0.958
PCR.4 Stable	3.560	0.9675	0.857	<0.001	0.771	0.943
Customer trust *(CT)*	3.67	0.839	—	—	—	—
CT.1 Hotels' services will make me feel a sense of security	3.522	1.0503	0.824	<0.001	0.738	0.910
CT.2 Hotels will provide quality services	3.603	0.9713	0.921	<0.001	0.836	1.006
CT.3 Services of hotels will be a quality-assurance process	3.644	1.0028	0.899	<0.001	0.814	0.984
CT.4 Hotels will be interested in their customers	3.901	0.8984	0.776	<0.001	0.689	0.862
Behavioral intention *(BI)*	3.63	0.832	—	—	—	—
BI.1 I would recommend hotels operating with AI to other people	3.709	0.9075	0.870	<0.001	0.785	0.956
BI.2 I would tell other people positive things about hotels operating with AI.	3.793	0.8618	0.860	<0.001	0.774	0.945
BI.3 I consider hotels operating with AI as my first choice compared to other hotels	3.416	1.0494	0.886	<0.001	0.801	0.972
BI.4 I have a strong intention to repeat visits to hotels operating with AI.	3.582	0.9684	0.896	<0.001	0.811	0.981