Heliyon 9 (2023) e16968

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Understanding the factors affecting AI services adoption in hospitality: The role of behavioral reasons and emotional intelligence

Hafiz Muhammad Wasif Rasheed [a], Yun Chen [b,*], Hafiz Muhammad Usman Khizar [c], Asif Ali Safeer [d]

[a] *School of Management, Department of Business Administration, Huazhong University of Science and Technology (HUST), Wuhan, China*
[b] *School of Business Administration, Hubei University of Economics, China*
[c] *School of Business Management and Administrative Sciences, The Islamia University of Bahawalpur (IUB), Punjab, Pakistan*
[d] *Business School, Huanggang Normal University, Huanggang, China*

A R T I C L E I N F O

Keywords:
Hospitality
Artificial intelligence
Adoption
Reasons
Behavioral reasoning theory

A B S T R A C T

This study explores the reasons (for and against) the adoption of AI in the hospitality industry among Pakistani customers. The hypothesis was tested using the sample obtained from Pakistani hospitality customers. The data is collected via an online survey and analyzed with the structural equation modeling and PROCESS macro. The study results indicate that cultural values positively associate reasons for, attitudes, and intentions to adopt. Moreover, the results prove that attitude mediates the relationship between reasons (for and against) and intention to adopt AI services in hospitality. Furthermore, the finding shows that customer emotional intelligence has no moderation effect on attitude and intention to adopt AI services. This study highlights technological complexity and safety concerns are the most significant barriers in the studied context. Further, addressing reason against (technological complexity and safety concerns) may allow policymakers to lessen the present customer attitude-intention gap by tackling the factors that cause customers to resist adopting AI services in hospitality. In this respect, marketers should develop a marketing campaign strategy focusing on the benefits of the adoption of AI services in comparison to employee service. This is the first empirical study examining cultural values, reasons (for and against) attitudes, their relationship with intentions, and moderating role of an attractive, important, yet ignored variable, customer emotional intelligence. This study confirms that the behavioral reasoning theory can better describe the customers' adoption behavior of AI services in the hospitality sector.

1. Introduction

In this era, technology is a game-changer for the hospitality sector. Innovative technologies such as AI, robots, and chatbots are changing the hospitality business [1,2]. AI technologies are starting to enter a variety of service sectors, including hotels, healthcare, and tourism [3,4]. According to the service classification order, the way customers adopt AI services may change based on the nature of the service sectors. The rise of AI is taking new opportunities and other benefits for tourism, hospitality, and other services sectors [5].

* Corresponding author.
E-mail address: chenyun@hbue.edu.cn (Y. Chen).

https://doi.org/10.1016/j.heliyon.2023.e16968
Received 30 December 2022; Received in revised form 30 May 2023; Accepted 2 June 2023
Available online 2 June 2023

For instance, it facilitates humans to complete their tasks efficiently by quickly going through self-check-in or out, hotel room services, housekeeping, concierge services, and chatbots interactions to collect the required information [6,7]. Moreover, it reduces human costs and improves service efficiency [8,9].

Many studies have been conducted at the national level to study the effect of cultural values on technology usage [10,11]. The cultural importance of users must be recognized when assessing technology acceptability and utilization. Previous findings in the AI adoption literature have led to a critical understanding of how consumers use AI through variables such as perceived usefulness, ease of use, and attitudes toward new technologies [12–15].

According to researchers, businesses must understand when, why, and whether customers would accept an innovation [16]. For this purpose, various theoretical perspectives can help professionals and researchers understand how any invention is adopted. Some examples include the theory of planned behavior, the theory of reasoned action, the technology acceptance modal, and the diffusion of innovation theory. Most of these frameworks are criticized for overlooking consumer resistance in favor of acceptance-related characteristics [16–18]. Previous researchers have indicated that new services and products have a high failure rate because there is a lack of attention paid to understanding the multiple causes of consumer resistance or the obstacles to their acceptance [18,19]. Comprehensive research determines that reasons for adopting and resisting innovation deviate qualitatively, impacting customers' decisions in multiple ways [18,20]. The reasons for opposing new inventions are not always the same as those for adoption.

This study aims to fill the gap by perceiving customers' behavioral reasoning processes associated with AI and reducing the gap using behavioral reasoning theory. This study contributes to the research on innovation resistance and adoption by implementing behavioral reasoning theory, allowing innovation researchers and management to examine the comparative effectiveness of reason for and against the adoption [21]. We used the previous research's subthemes of reasons for and against [22]. The primary research objective is to discover the reasons (for and against) affect relations between cultural values, attitudes, and intention to adopt/use AI services in the hospitality sector. Also, customers' emotional intelligence moderates these relations. Examining these conditions is important as it helps practitioners and researchers understand how customers' emotional intelligence affects the drivers of adopting AI services. For this purpose, data were collected from Pakistani hospitality customers and analyzed to address these objectives.

This study is structured into five sections. After the introductory section, we provide the literature, theory, and hypothesis development. Using a sample of 480 Pakistani customers, the model is tested via structural equation modeling in the next step. Finally, the results are discussed, providing future research directions with implications.

2. Literature

Service robots reflect AI that differs from existing technology. Robots are physical devices that can execute certain tasks due to autonomy, mobility, and sensory capabilities [23]. A service robot is a mixture of AI technology, service-oriented features, and customer values, and overall performance, public awareness, and customer acceptability are key indicators of robot quality [24]. Past researchers have attempted to explore consumers' attitudes and actions toward using AI technology in services; however, most of these were constructed on traditional technological acceptance theories [2,25]. Previous studies mostly focused on consumer behavior in many areas, containing organic food [17], positive or resistive consumer perceptions of innovations [18], alcohol over-consumption [25], managerial policymaking [26], and mobile banking adoption [27]. Existing research has given little attention to the impact of cultural values on customers' attitudes and intentions to adopt AI. This study contributes to the adoption of AI services in the hospitality industry by using and improving a novel behavioral concept for BRT [21]. To explore the integrated effects of both reasons on adopting AI services, the effect of cultural value on customers' reasoning process and attitude toward adopting AI services in hospitality sector.

2.1. *Behavioral reasoning theory*

The BRT is the first theory explaining reasons, beliefs, global motives, and behavioral intentions [21]. According to this theory, positive variables can explain why people perform particular behaviors but cannot anticipate why they would resist that behavior. As a result, Westaby [21] proposed that it is necessary to discover the unfavorable variables that drive persons to avoid adopting particular behaviors. These subjective aspects are theoretically diverse, depending on how customers perceive their values and beliefs. Reasons can affect the ability to affect customers' attitudes in a complementary manner, and their explanations can provide perceptions into situational or contextual decision-making [21,26,28].

BRT differentiates among values, beliefs, and the effect of these aspects on motives. Beliefs and values can be detained for a long run and deep-rooted, in contrast to reasons relevant to decision-making [17,21,26]. These may affect global drives, customers' reasoning processes, and their anticipated course of action [21,28]. In the novelty perspective of BRT, many scholars used this to study customer behavior in several contexts, such as organic food consumption [28] and organic food purchase [17]. Further research shows favorable or resistive customer perceptions of innovations [18], over-consumption of alcohol [25], entrepreneurial behavior of nations [29], mobile banking adoption [27], and managerial policymaking [26].

Based on BRT, this study intends that cultural values will impact both reasons (H1a, H1b), attitudes, and intentions to adopt/use (H2, H3). Attitude directly affects intention (H4). Both directly and indirectly affect attitudes and customers' adoption intentions (H5a, H5b, H6a, H6b). Consumer reasons (for and against) will mediate the role of cultural values, attitudes, and intention to adopt/use AI services (H7a, H7b, H7c, H7d). Attitude will mediate the role of cultural values, both reasons and intention to adopt/use AI services (H8a, H8b, H8c). It was also proposed that customer emotional intelligence moderates the relation between reasoning and intention to adopt/use and the association between attitude and intention to adopt/use (H9a, H9b, H9c). The following section provides the theoretical explanation for the conceptual framework's linkage among each construct.

2.2. Research hypothesis

2.2.1. Cultural values → reasons

According to Calza, Cannavale [29], cultural values positively affect both reasons for entrepreneurial intention. Values have a significant relationship between reasons for and against organic food purchases [17]. Values were linked with reasons for purchasing organic food products, subject to the brand label's reputation and esteem [28]. This discussion has resulted in the following hypothesis.

H1a. Cultural values positively relate to their reasons for the adoption/use of AI services.

H1b. Cultural values negatively relate to their reasons against the adoption/use of AI services.

2.2.2. Cultural values → attitudes, and intentions

Previous studies show that values and attitude also proposed an association among values, attitude, and behavior that causality proceeds from values to behavior [27]. Value significantly links the attitude and plays a significant role in decision-making since it affects customers' attitudes about a service or product [18]. According to some studies, values positively and directly affect customers' attitudes toward organic food consumption [30]. Some researchers' results indicate that values negatively link attitudes and conflict with previous results [17]. This discussion has resulted in the following hypothesis.

H2. Cultural values are directly associated with consumers' attitudes.

H3. Cultural values are directly associated with their intention to adopt/use AI services.

2.2.3. Attitude → intentions

Some researchers find that attitudes positively correlate with customer intentions [17,31]. According to Claudy, Garcia [18], customers' attitudes about car-sharing and micro wind turbine usage positively correlate with their adoption intentions. Customers' attitudes about organic food significantly correlate with their purchase intention [17]. Also, a reasonable consumer attitude toward e-waste recycling is expected to be connected with an increase in intention to e-waste recycling [32]. This discussion has resulted in the following hypothesis.

H4. Consumers' attitudes are positively associated with their intention to adopt/use AI services.

2.2.4. Reasons → attitude, and intentions

Previous researchers found that 'reasons for' were a significant factor that affected customer behavior in many contexts [17,26,33]. Moreover, as earlier stated, 'reasons for' positively correlate with attitude, whereas 'reasons against' have a negative relationship [17,18]. Reasons for eating organic food were significantly related to customer attitudes and intents [17]. Literature showed the prevalence of a less-established field of study focusing on consumer barriers to organic food purchase [34]. The reasons against are generally discussed as the resistors, which can create negative consumer perceptions about engaging in a particular behavior [33]. This discussion has resulted in the following hypothesis.

H5a. Consumer reasons for adoption/use of AI services are positively associated with their attitudes.

H5b. Consumer reasons against the adoption/use of AI services are negatively associated with their attitudes.

H6a. Consumer reasons for using AI services have been positively associated with the intention to adopt AI services.

H6b. Consumer reasons against using AI services have been negatively associated with the intention to adopt AI services.

2.2.5. Mediating role of reasons

Previous research has shown that some reasons significantly affect the relationship between values and attitudes [30]. Some researchers' results show reasons for and against performing the mediators' role and supporting the BRT results. Customers' reasoning processes affect customer value and attitudes [17,30,35]. This discussion has resulted in the following hypothesis.

H7a. Consumer reasons for adopting AI services mediate the association between cultural values and attitudes.

H7b. Consumer reasons against adopting AI services negatively mediate the association between cultural values and attitudes.

H7c. Consumer reasons for adopting AI services positively mediate the association between cultural values and intention to use AI services.

H7d. Consumer reasons against the adoption/use of AI services negatively mediate the association between cultural values and intention to use AI services.

2.2.6. Mediating role of attitude

Most previous studies focused on behavioral intention rather than the behavior itself because external reasons might affect the relationship between the two dimensions. Intention can affect a customer's future decision to engage in specific behaviors. Some other researchers found that attitudes affect a person's intention to use Halal food, reflected in their consumption behavior [36]. On behalf of arguments, this study hypothesizes that.

H8a. Consumers' attitudes positively mediate the association between cultural values and intention to adopt/use AI services.

H8b. Consumers' attitudes positively mediate the relationship between consumer reasons for adoption/use of AI services and intention to adopt/use AI services.

H8c. Consumers' attitudes towards intention to use AI services negatively mediate the relationship between consumer reasons against adoption/use of AI services and intention to adopt/use AI services.

2.2.7. Moderating role of customer emotional intelligence

Emotional intelligence (EI) is an individual's skills to recognize, understand, utilize, and control their and others' emotions [37]. Emotional factors positively correlate with customer attitudes, behavior, and intention [38,39]. Emotional intelligence positively moderates the relationships between customers' attitudes, perceived behavioral control, subjective norms, and purchasing intention in luxury fashion products [40]. This discussion leads to the following hypothesis.

H9a. Customer emotional intelligence moderates the association between consumer reasons for adoption and intention to adopt/use AI services.

H9b. Customer emotional intelligence negatively moderates the association between consumer reasons against the adoption and intention to adopt/use AI services.

H9c. Customer emotional intelligence positively moderates the association between consumer attitude and intention to adopt/use AI services.

We proposed the conceptual model on the above hypotheses base, as shown in Fig. 1.

3. Method

3.1. Data collection strategy

In this study, we used the positivist paradigm approach. The positivist paradigm is a research paradigm that emphasizes objectivity, empiricism, and the scientific method. It assumes that a single reality can be objectively observed, measured, and understood through systematic and rigorous scientific inquiry. In studying consumer adoption of AI in the hospitality sector, the positivist paradigm would involve using quantitative methods to collect and analyze data to test hypotheses and establish causal relationships between variables.

This study created a self-administered questionnaire in English and posted it on Facebook and WhatsApp to collect the data from intended customers in Pakistan in October and November 2022. In this questionnaire, first, we explained the study's aim and the key

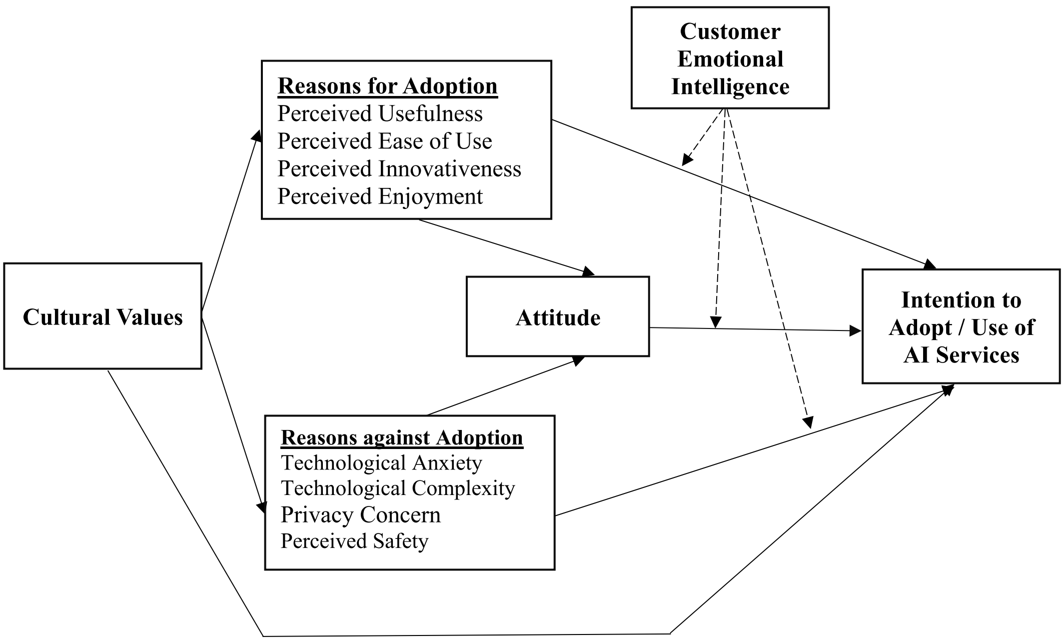

Fig. 1. Conceptual model.

concepts for participants' understanding. Participants voluntarily participate in this online survey. We confirmed the privacy of our respondents to decrease the socially desired responses and improve the respondent sincerity.

3.2. Sample

Our prospective survey subjects are Pakistani hospitality customers who have used AI services in the hospitality sector. The online survey was held in Pakistan. We computed the minimal sample size required for the study to be 384 with a sampling error of no more than 5% [41]. So our sample size between 300 and 500 is appropriate for variance-based SEM. The respondents filled out the 520 questionnaires. After initial analysis, we found that only 480 questionnaires were helpful for the research, with a 92.3% response rate. Respondent's gender, age, and education are the controlled variables. We used the SPSS and AMOS 24 software to analyze the data. Table 1 shows the gender information of the respondents, Table 2 shows the respondent's age, and Table 3 presents the education of the respondents.

3.3. Measures

The questionnaire was divided into two sections. The first section linked to the respondents' profiles (gender, age, and education); the other area had 50 items. Each measurement item in Table 4 uses a five-point Likert scale, from 1 = strongly disagree to 5 strongly agree.

3.4. Reliability and validity

We employed previously validated items, which helped confirm our construct measure's validity. The study aims to establish instrument validity and reliability, including discriminant and convergent validity, average variance extracted (AVE), Cronbach's alpha (CA), composite reliability (CR), and factor loadings, by following the standards of [52]. As seen in Table 5, the values of AVE (0.681–0.866), CR (0.905–0.970), and CA (0.902–0.967) are within acceptable limits and fulfill the validity and reliability cutoff requirements. Similarly, factor loadings are greater than 0.70 and have met the 0.60 criterion for satisfactory convergent validity of scales proposed by Ref. [53].

Jee-Hoon and Hye-Ji [54] described that CR values (0.806–0.970) exceeded the recommended values and showed high consistency and reliability. According to some studies, CA and CR values greater than 0.9 and less than 0.95 are good and show high consistency and reliability [55–57]. Furthermore, If a reverse-coded question was used, the data feedback process changed it in the same direction, and the alpha reliability coefficient of the scale was also increased [58]. On the other hand, some researchers described that if CA and CR values are too high, it can be an indication of redundant items or overfitting of the model. In other words, it suggests that the items in the scale are measuring the same construct too closely or that the model is being overfitted to the data. It is generally recommended to remove any redundant items to improve the validity and generalizability of the results. Additionally, it is important to consider the AVE values, which indicate the amount of variance captured by the items in relation to their respective latent variable. AVE values above (0.4–0.7) are considered acceptable, and all the AVE values in the study meet this criterion [59,60].

4. Results

We checked the data normality through the values for skewness, andkurtosis was calculated and found that it is lesser than ±1. The deviation confirmed the normal distribution of the data collected. This study used the commonly applied covariance-based structural equation modeling (CB-SEM) for confirmatory or explanatory research. CB-SEM is preferred when testing the theory, confirming or comparing other theories. Confirmatory factor analysis (CFA) was used to measure the discriminant and convergent validity of the six components identified in Table 5. The CFA findings showed that the model with six features fit well (X^2 = 3346.724, degrees of freedom (df) = 1146, comparative fit index (CFI) = 0.917, standardized root mean square residual (SRMR) = 0.060), root mean square error of approximation (RMSEA) = 0.063 [53]. At the 0.001 level, all standardized loadings differed significantly from zero, and all items were loaded on their corresponding latent constructs, indicating convergent validity (see Table 5). It shows the average variance extracted, and the values were more than 0.60. The inter-correlation between the two constructs was smaller than the square root of the AVE values for all pairings of constructs (see Table 6), indicating discriminant validity.

4.1. Testing of hypothesis

We tested the hypotheses using the Hayes [64] developed PROCESS macro. It is a modeling tool for perceived variable ordinary

Table 1
Gender information of the respondents.

Valid	Frequency	Percent
Male	230	47.9
Female	250	52.1
Total	480	100.0

Table 2
Age information of the respondents.

Valid	Frequency	Percent
<25 years	118	24.6
25–33 years	267	55.6
34–42 years	75	15.6
>42 years	20	4.2
Total	480	100.0

Table 3
Education information of the respondents.

Valid	Frequency	Percent
HSSC or Below	24	5.0
Bachelor	203	42.3
Master	192	40.0
Other	61	12.7
Total	480	100.0

least squares regression (OLS) and logistic regression route analysis. It evaluates direct and indirect effects in one and multi-mediators (serial and parallel). Moderation models include two and three-way relationships, simple slopes, and areas of significance used to investigate interactions and conditional indirect outcomes involving one or more mediators or moderators.

Table 6 indicates the correlation matrix and the measurements' descriptive statistics. Table 7 shows the regression results (direct effects) of this study. Cultural values positively related to the reasons for adopting AI services ($b = 0.477$, $p < 0.000$), supporting H1a. Cultural values significantly and negatively related the reasons against adopting AI services ($b =$ - 0.527, $p < 0.000$), supporting H1b. Cultural values positively related to the attitude ($b = 0.231$, $p < 0.000$), supporting H2. Cultural values positively related to the intention to use AI services ($b = 0.109$, $p < 0.044$), supporting H3. Consumers' attitudes positively related to adopting AI services ($b = 0.103$, $p < 0.036$), supporting H4. The reasons for adopting AI services positively related to attitudes ($b = 0.114$, $p < 0.008$), supporting H5a. Reasons against the adoption negatively related the attitudes ($b =$ - 0.342, $p < 0.000$), supporting H5b. Reasons for adopting AI services positively related to the intention to use the AI services ($b = 0.099$, $p < 0.035$), keeping H6a. Reasons against adopting AI services negatively related to the intention to adopt the AI services ($b =$ - 0.256, $p < 0.035$), supporting H6b. Table 8 shows the mediation results (indirect effects) of this study. Moreover, reasons for adopting AI services mediate the relationship between cultural values and attitude because the 95% CI (0.095, 0.194) for an indirect effect, not including zero, supports H7a. Reasons against adopting AI services mediate the association between cultural values and intention to adopt AI services because the 95% CI (0.160, 0.265) supports H7b. Reasons for adopting AI services mediate the association between cultural values and intention to use AI services because the 95% CI (0.083, 0.185) supports H7c. Reasons against adopting AI services mediate the association between cultural values and intention to use AI services because the 95% CI (0.129, 0.227) supports H7d.

Attitude mediates the association between cultural values and intention to adopt AI services because the 95% CI (0.147, 0.061) supports H8a. Attitude mediates the association between reasons for adopting AI services and intention to adopt/use AI services because the 95% CI (0.138, 0.051) supports H8b. Attitude mediates the association between reasons against adopting AI services and intention to use AI services because the 95% CI (−0.024, −0.133) supports H8c. Table 9 presents the results of moderating role of customer emotional intelligence and the association between reasons for the adoption and intention to adopt/use AI services. Both were significantly correlated positively ($b = 0.102$, p 0.044), which supported H9a. The moderating impact of customer EI on the other factors is indicated in Figs. 2 and 3. The moderating role of customer EI is shown in Table 10, and the correlation between reasons against adoption and intention to adopt/use AI service. Both supported H9b with having a significant negative correlation ($b =$ - 0.203, p 0.000). The moderating influence of customer emotional intelligence in the relationship between attitude and intention to use AI services is shown in Table 11. Results do not support H9d because there is no significant relationship ($b = 0.017$, p 0.685).

5. Discussion

This study explores the consumer adoption of AI services in the Pakistani hospitality sector. As a theoretical lens, this study used the behavioral reasoning theory. The developed model explores the relationship between cultural values, reasons, and attitudes toward the consumer adoption of AI services. In addition, the relationship between reasons and intentions was also examined. This study uses the PROCESS macro method to test the research model with a sample of 480 Pakistani customers.

The study results indicate that H1a, H2, and H3 values positively associate the reasons for, attitudes, and intentions to use AI services, and these findings are supported by previous research [27,28]. H5a and H6a results show that reasons for adoption have positive associations with attitudes and intentions to adopt AI services. BRT confirmed that the reasons for adopting have a positive association between attitude and intentional behavior [17,18,26]. On the other hand, H5b and H6b results show that reasons have negative associations with attitudes and intentions to adopt AI services. Findings are consistent with the earlier studies' findings in different contexts [27,28]. Similarly, the findings of the previous studies validate that consumer reasons (for and against) will mediate

Table 4
Measurement.

Construct	Items	Items details with modifications	Source
Uncertainty Avoidance (Cultural Values)	UA1	Instructions for operations are important	[42]
	UA2	It is critical to strictly adhere to instructions and procedures.	
	UA3	Standardized procedures for work are helpful.	
	UA4	It's critical to have precise instructions and always know what I'm supposed to do.	
Collectivism (Cultural Values)	CO1	Individuals should sacrifice their interests for their groups.	[42]
	CO2	Individuals should remain with the group even when things go tough.	
	CO3	Personal success is less important than group success.	
	CO4	Group loyalty would be promoted even if my personal goals suffer.	
Masculinity (Cultural Values)	MA1	A professional career is more important for males than for women.	[42]
	MA2	Some tasks are always better performed by males than a woman.	
	MA3	Men generally solve issues by logical analysis, but women typically solve problems through intuition.	
Perceived Ease of Use	PEU1	Learning to deal with AI devices in hotels would be easy for me.	[12,15,43]
	PEU2	My interactions with AI devices in hotels would be clear and understandable.	
	PEU3	My interactions with AI devices in hotels would not require much mental effort.	
	PEU4	Overall, I believe AI devices are easy to use.	
Perceived Usefulness	PU1	Using AI devices will be useful for me to carry out my requests.	[12,15,43]
	PU2	The AI devices will assist me in saving the necessary service time.	
	PU3	The robot will properly manage a line.	
Perceived Enjoyment	PE1	I enjoy using AI services in hotels	[44,45]
	PE2	I like to use new technologies in hotels.	
	PE3	I feel excited when I use robotic services in hotels.	
Perceived Innovativeness	PI1	Robotic services seem new	[46]
	PI2	Robotic services seem creative.	
	PI3	Robotic services seem innovative.	
Technological Complexity	TC1	Robotic services consist of a high number of components.	[47]
	TC2	Robotic services, a vast number of functions are compromised.	
	TC3	Robotic services are always very new.	
	TC4	The interconnectedness within AI/technology is high.	
Technological Anxiety	TA1	Using technology such as robots for hospitality makes me anxious	[48,49]
	TA2	I find it tough to understand technological issues.	
	TA3	I escape from using robotic technologies as they are unfamiliar to me.	
	TA4	I am apprehensive about using technology as I cannot rectify mistakes.	
Perceived Safety	PS1	I believe that using the robot service is risky.	[50]
	PS2	Using the robots requires increased attention.	
	PS3	I feel safe while using the robotic service.	
	PS4	I can use AI technologies without looking at them.	
Privacy Concern	PC1	I consider my data is safe when using AI services	[12,15,43]
	PC2	My data will be kept secure by using robotic services.	
	PC3	My financial transaction records through the robot will be protected.	
	PC4	The robots handling staff share my personal information with other companies.	
Attitude	AT1	Using AI devices is positive for me	[12,15,43]
	AT2	It is useful to have a service robot.	
	AT3	For me, using AI technology is a pleasurable experience.	
Customer Emotional Intelligence	CEI1	Most of the time, I have a good sense of why I have a certain feeling.	[51]
	CEI2	I have a decent command of my feelings.	
	CEI3	I am aware of the way I react.	
	CEI4	I am fairly good at controlling my emotions.	
Intention to Use of AI Services (Behavioral Intention)	AIS1	I am going to use the robot services to place my orders.	[12,15,43]
	AIS2	I will utilize the robot to look up product details.	
	AIS3	I intend to make my payment via the robot.	

the role of values, attitudes, and intentions (H7a, H7b, H7c, H7d). Also, attitude mediates the role of values, both reasons and intentions (H8a, H8b, H8c) [21,26,34]. The findings of the moderation analysis indicate that H9a customer emotional intelligence had a positive association between reasons for the adoption and intention to adopt/use AI services. Furthermore, H9b customer emotional intelligence had a positive association between reasons for the adoption and intention to adopt/use AI services. H9c results show no significant relationship between attitude and the intention to adopt/use AI services.

5.1. Theoretical implications

This study has significantly prolonged the scope of empirical analyses on customer AI adoption behavior. This is the first empirical study examining consumer values, barriers, or resistance to adopting AI services and their relationship with intentions. In addition, the current research has extended the theoretical grounds of the previous literature by using the BRT in the context of adopting AI services in hospitality industry. It opens the scope of previous theoretical investigations into using AI services behavior, especially in Pakistani hospitality. Applying the BRT framework increases the knowledge by finding the parallel outcome of context-specific reasons that impact the Pakistani customers' decision to use or resist AI services.

Table 5
Reliability and validity results.

Variables	Items	Factor Loadings	Cronbach's Alpha	CR	AVE
Cultural Values	CV1	.835	.908	.911	.694
	CV2	.739			
	CV3	.721			
	CV4	.672			
	CV5	.749			
	CV6	.685			
	CV7	.715			
	CV8	.774			
	CV9	.759			
	CV10	.996			
	CV11	.988			
Reasons for Adoption	RFA1	.846	.956	.9594	.716
	RFA2	.781			
	RFA3	.864			
	RFA4	.851			
	RFA5	.827			
	RFA6	.879			
	RFA7	.849			
	FFA8	.857			
	RFA9	.861			
	RFA10	.842			
	RFA11	.859			
	RFA12	.867			
	RFA13	.813			
Reasons Against Adoption	RAA1	.872	.965	.968	.681
	RAA2	.833			
	RAA3	.790			
	RAA4	.720			
	RAA5	.742			
	RAA6	.792			
	RAA7	.812			
	RAA8	.832			
	RAA9	.858			
	RAA10	.811			
	RAA11	.768			
	RAA12	.833			
	RAA13	.819			
	RAA14	.806			
	RAA15	.825			
	RAA16	.831			
Attitude	ATT1	.832	.902	.905	.762
	ATT2	.891			
	ATT3	.842			
Customer Emotional Intelligence	CEI1	.836	.894	.897	.810
	CEI2	.886			
	CEI3	.899			
	CEI4	.904			
Intention to Adopt/Use AI Services	AIS1	.912	.908	.911	.866
	AIS2	.898			
	AIS3	.921			

Notes. CV1, CV2, etc., are items for measuring cultural values. RFA1, RFA2, etc., are items for measuring reasons for adoption. RAA1, RAA2, etc., are items for measuring reasons against adoption. ATT1, ATT2, etc., items for measuring attitude. CEI1, CEI2, etc., items for measuring customer emotional intelligence. AIS1, AIS2, etc., items for measuring intention to adopt/use AI services.

Table 6
Descriptive statistics and correlation matrix.

	Mean	SD	1	2	3	4	5	6	7	8	9
1. CV	3.92	1.08	.010	.010	−.001	***.771***					
2. RFA	4.07	1.07	.064	.014	−.047	.005	***.846***				
3. RAA	1.89	.98	−.077	.022	.088	−.005	−.006	***.810***			
4. ATT	3.95	1.13	.001	.070	−.064	.005	.004	−.005	***.873***		
5. CEI	4.02	1.13	.025	−.036	−.054	.005	.005	−.006	.004	***.900***	
6. AIS	4.18	1.20	.051	.013	−.019	.003	.004	−.004	.003	.003	***.931***

Notes: n = 480. *p < 0.05, **p < 0.01. SD = Standard deviation. CV = Cultural values, RFA = Reasons for adoption, RAA = Reasons against adoption, ATT = Attitude, CEI = Customer emotional intelligence, and AIS = intention to adopt/use AI services.

Table 7
Regression results (Direct effects).

			Estimate	p-value
RFA	←	CV	.477	.000
RAA	←	CV	−.527	.000
A	←	CV	.231	.000
A	←	RFA	.114	.008
A	←	RAA	−.342	.000
AIS	←	A	.103	.036
AIS	←	RAA	−.256	.000
AIS	←	RFA	.099	.035
AIS	←	CV	.109	.044

Note: CV = Cultural values, RFA = Reasons for adoption, RAA = Reasons against adoption, A = Attitude, CEI = Customer emotional intelligence, and AIS = intention to adopt/use AI services.

Table 8
Mediation results (Indirect effects).

Path	Indirect effect	Upper-Bond Confidence Interval 95%	Lower-Bond Confidence Interval 95%	*p*-value	Decision
CV→RFA→A	.134	.194	.095	.005	Supported
CV→RAA→ A	.209	.265	.160	.007	Supported
CV→RFA→AIS	.121	.185	.083	.006	Supported
CV→A→AIS	.102	.147	.061	.012	Supported
CV→RAA→AIS	.182	.227	.129	.010	Supported
RFA→A→AIS	.094	.138	.051	.007	Supported
RAA→A→AIS	.-.076	−.024	−.133	.011	Supported

Note: CV = Cultural values, RFA = Reasons for adoption, RAA = Reasons against adoption, A = Attitude, CEI = Customer emotional intelligence, and AIS = intention to adopt/use AI services.

Table 9
Moderation effect of customer emotional intelligence between reasons for adoption and intention to adop/use AI services.

Outcome: AIS	β	*p*
Constant	4.124	.000
RFA	.387	.000
CEI	.125	.031
RFA x CEI	.102	.044

Note: RFA = Reasons for adoption, CEI = Customer emotional intelligence, and AIS = intention to adopt/use AI services.

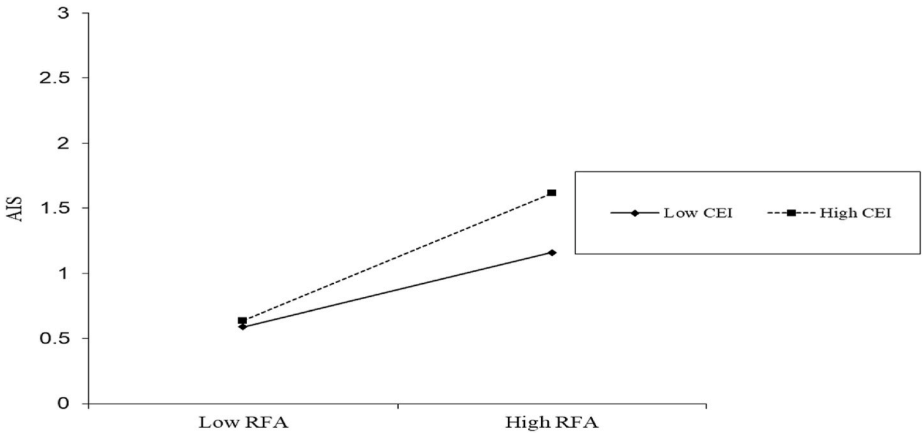

Fig. 2. The moderating effect of customer emotional intelligence on the reasons for adoption-intention to adopt/use AI services.

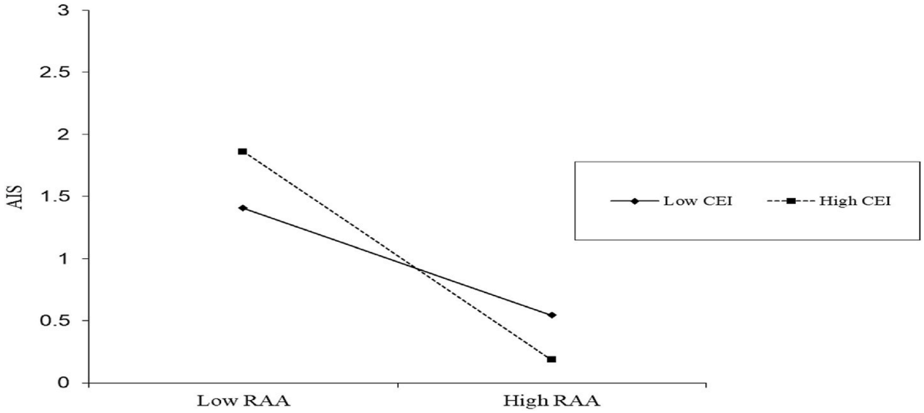

Fig. 3. The moderating effect of customer emotional intelligence on the reasons against adoption-intention to adopt/use AI services.

Table 10
Moderation effect of customer emotional intelligence between reasons against adoption and intention to adop/use AI services.

Outcome: AIS	β	*p*
Constant	4.054	.000
RAA	−.634	.000
CEI	.024	.656
RAA x CEI	−.203	.000

Note: RAA = Reasons against adoption, CEI = Customer emotional intelligence, and AIS = intention to adopt/use AI services.

Table 11
Moderation effect of customer emotional intelligence between attitude and intention to adop/use AI services.

Outcome: AIS	β	*p*
Constant	4.171	.000
Attitude	.294	.000
CEI	.148	.007
Attitude x CEI	.017	.685

Note: CEI = Customer emotional intelligence, and AIS = intention to adopt/use AI services.

This study emphasizes the significance of customer characteristics such as cultural values. Suppose the hotel management wants to implement new technologies for customer adoption. In that case, they should consider cultural importance because each customer has diverse cultural values and may feel differently about AI adoption. Furthermore, this study tested the moderating role of an essential, interesting, yet ignored variable, customer emotional intelligence. These outcomes should inspire other researchers to conduct related studies between other geographical and cultural groups to understand this topic better.

5.2. Practical implications

This study provides practical implications for managers, practitioners, and marketers. Hospitality businesses are expanding their business overseas. Most practitioners believed their guests hold collectivist or high power distance cultural values [61]. This is not sensible to think that all customers share the same cultural values without doing an in-depth investigation. Actual analyses of individual cultural values will provide more precise and truthful facts about their customers. Practitioners who are aware of changes in the cultural values of their customers will thrive in the hospitality industry with more favorable feedback. This research indicates that technological complexity and safety concerns are the most significant barriers in the studied context. Further, addressing reasons against technological complexity and safety concerns may allow policymakers to lessen the present customer attitude and intention gap by tackling the aspects that cause customers to resist adopting AI services in hospitality.

Enhancing customer experiences by implementing AI-powered solutions in the hospitality sector, businesses can significantly enhance customer experiences [62]. Chatbots that users can respond to client inquiries quickly and accurately, while personalized recommendations based on past preferences can help businesses offer tailored experiences to their customers. AI can also help hospitality businesses improve their operational efficiency. Businesses can reduce their workload by automating routine tasks such as room bookings and check-ins, freeing staff to focus on more complex tasks. Implementing AI-powered solutions can also lead to cost savings in the hospitality sector. Businesses can save on labor costs by reducing the need for staff to perform routine tasks.

Additionally, AI can help optimize energy consumption, reducing utility bills. Adopting AI-powered solutions in the hospitality industry, those who fail to keep up with risk being left behind. Implementing AI-powered solutions might assist organizations in gaining a competitive advantage as customers want more personalized and efficient service. Furthermore, ethical issues must be taken into consideration. Businesses should verify that the data used to train AI models is acquired ethically and that AI is not utilized discriminatorily.

5.3. Conclusion, limitations, and future research directions

The use of AI services in hospitality has advantages and disadvantages, which firms must consider when deciding whether to implement AI technology. The findings of this study, which are based on behavioral reasoning theory, give a valuable foundation for understanding the reasons for both positive and negative attitudes toward AI in hospitality. On the one hand, AI can improve the customer experience, reduce costs and increase efficiency, all desirable outcomes for the hospitality industry [22]. The concerns about reasons against adoption (technological complexity, anxiety, privacy concerns, perceived safety) and security issues may outweigh these benefits for some customers. Ultimately, adopting AI in hospitality should be based on carefully evaluating the potential risks and benefits and the customers' and employees' needs and preferences.

The current study also has limitations. An online questionnaire and a limited sample size of customers who have direct experience with AI in this context were employed in the present research. The findings of this research originate from the Pakistan hospitality sector. Due to differences in points of view, trust in technology, and customer demands, adopting AI in the hospitality sector could vary across cultures. A cross-cultural comparison of consumer acceptance of AI in the hospitality sector may be required to comprehensively understand the phenomena. While most studies on customer adoption of AI in hospitality have focused on the benefits of AI, there is limited research on the negative outcomes of AI adoption. Future research should explore potential negative outcomes such as job displacement and the impact on human-to-human interactions. Future research should employ a multi-method approach to studying customer adoption of AI in hospitality. This would involve mix-methods to obtain a more comprehensive understanding of the phenomenon. Future research should integrate ethical considerations into studying customer adoption of AI in hospitality [63]. This would involve exploring the ethical implications of AI adoption in the sector, such as the impact on jobs and the potential for discriminatory practices. This would ensure that the benefits of AI adoption in the sector are balanced against potential ethical concerns.

Future studies include understanding how reasons (for and against) interpret AI adoption intentions in less advanced or rural areas. Such focus is mainly directed at identifying more context-specific causes influencing intentions to use AI services in developed vs. rural areas. Future studies will determine the reasons for adopting AI services and examine their relationships with cultural values and adopting AI services in the tourism sector. Future studies should use more and new moderators on different perspectives. From the customer perspective, there is a desire to share and a desire to use a product perspective like product credibility, product trialability, and product attributes. Future studies combine the behavioral reasonning theory with other theories, like innovation diffusion theory or models like technology acceptance model, for more accurate implications.

Author contribution statement

Hafiz Muhammad Wasif Rasheed: Conceived and designed the analysis; Collected the data; Contributed data or analysis tools; Performed the analysis; Wrote the paper.

Yun Chen: Conceived and designed the analysis; Contributed data or analysis tools.

Hafiz Muhammad Usman Khizar:Collected the data; Contributed data or analysis tools; Wrote the paper.

Asif Ali Safeer: Collected the data; Performed the analysis; Wrote the paper.

Data availability statement

Data will be made available on request.

Additional information

Supplementary content related to this article has been publish online at [URL].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e16968.

References

[1] J. Bowen, C. Morosan, Beware hospitality industry: the robots are coming, Worldwide Hospitality Tourism Themes 10 (6) (2018) 726–733.
[2] I. Tussyadiah, A review of research into automation in tourism: launching the annals of tourism research curated collection on artificial intelligence and robotics in tourism, Ann. Tourism Res. 81 (2020), 102883.
[3] S. Ivanov, et al., Progress on robotics in hospitality and tourism: a review of the literature, Journal of Hospitality and Tourism Technology 10 (4) (2019) 489–521.
[4] C.-E. Yu, H.F.B. Ngan, The power of head tilts: gender and cultural differences of perceived human vs human-like robot smile in service, Tour. Rev. 74 (3) (2019) 428–442.
[5] L. Wu, et al., Robotic involvement in the service encounter: a value-centric experience framework and empirical validation, J. Serv. Manag. 32 (5) (2021) 783–812.
[6] M.O. Parvez, Use of machine learning technology for tourist and organizational services: high-tech innovation in the hospitality industry, J. Tourism Futur. 7 (2) (2021) 240–244.
[7] M. Li, et al., A systematic review of AI technology-based service encounters: implications for hospitality and tourism operations, Int. J. Hospit. Manag. 95 (2021), 102930.
[8] S. Ivanov, C. Webster, P. Seyyedi, Consumers' attitudes towards the introduction of robots in accommodation establishments, Tourism Int. Interdiscipl. J. 66 (3) (2018) 302–317.
[9] S.H. Ivanov, C. Webster, K. Berezina, Adoption of robots and service automation by tourism and hospitality companies, Revista Turismo Desenvolvimento 27 (28) (2017) 1501–1517.
[10] S.-H. Kim, et al., Hospitality employees' citizenship behavior: the moderating role of cultural values, Int. J. Contemp. Hospit. Manag. 30 (2) (2018) 662–684.
[11] S. Sun, et al., The impact of cultural values on the acceptance of hotel technology adoption from the perspective of hotel employees, J. Hospit. Tourism Manag. 44 (2020) 61–69.
[12] R. Davis, D. Wong, Conceptualizing and measuring the optimal experience of the eLearning environment, Decis. Sci. J. Innovat. Educ. 5 (1) (2007) 97–126.
[13] N. Marangunić, A. Granić, Technology acceptance model: a literature review from 1986 to 2013, Univers. Access Inf. Soc. 14 (1) (2015) 81–95.
[14] I. Ajzen, M. Fishbein, Attitude-behavior relations: a theoretical analysis and review of empirical research, Psychol. Bull. 84 (5) (1977) 888.
[15] S.S. Park, C.D. Tung, H. Lee, The adoption of AI service robots: a comparison between credence and experience service settings, Psychol. Market. 38 (4) (2021) 691–703.
[16] A.K. Sahu, R. Padhy, A. Dhir, Envisioning the future of behavioral decision-making: a systematic literature review of behavioral reasoning theory, Australas. Mark. J. 28 (4) (2020) 145–159.
[17] A. Tandon, et al., Behavioral reasoning perspectives on organic food purchase, Appetite 154 (2020), 104786.
[18] M.C. Claudy, R. Garcia, A. O'Driscoll, Consumer resistance to innovation—a behavioral reasoning perspective, J. Acad. Market. Sci. 43 (4) (2015) 528–544.
[19] M. Antioco, M. Kleijnen, Consumer adoption of technological innovations: effects of psychological and functional barriers in a lack of content versus a presence of content situation, Eur. J. Market. 44 (11/12) (2010) 1700–1724.
[20] M. Kleijnen, N. Lee, M. Wetzels, An exploration of consumer resistance to innovation and its antecedents, J. Econ. Psychol. 30 (3) (2009) 344–357.
[21] J.D. Westaby, Behavioral reasoning theory: identifying new linkages underlying intentions and behavior, Organ. Behav. Hum. Decis. Process. 98 (2) (2005) 97–120.
[22] H.M.W. Rasheed, et al., Exploring Consumer-Robot interaction in the hospitality sector: unpacking the reasons for adoption (or resistance) to artificial intelligence, Technol. Forecast. Soc. Change 192 (2023), 122555.
[23] J. Murphy, C. Hofacker, U. Gretzel, Dawning of the age of robots in hospitality and tourism: challenges for teaching and research, European Journal of Tourism Research 15 (2017) (2017) 104–111.
[24] H. Bae, J.-H. Oh, Biped robot state estimation using compliant inverted pendulum model, Robot. Autonom. Syst. 108 (2018) 38–50.
[25] P. Norman, M.T. Conner, C.B. Stride, Reasons for binge drinking among undergraduate students: an application of behavioural reasoning theory, Br. J. Health Psychol. 17 (4) (2012) 682–698.
[26] J.D. Westaby, T.M. Probst, B.C. Lee, Leadership decision-making: a behavioral reasoning theory analysis, Leader. Q. 21 (3) (2010) 481–495.
[27] A. Gupta, N. Arora, Consumer adoption of m-banking: a behavioral reasoning theory perspective, Int. J. Bank Market. 35 (4) (2017) 733–747.
[28] J. Ryan, R. Casidy, The role of brand reputation in organic food consumption: a behavioral reasoning perspective, J. Retailing Consum. Serv. 41 (2018) 239–247.
[29] F. Calza, C. Cannavale, I.Z. Nadali, How do cultural values influence entrepreneurial behavior of nations? A behavioral reasoning approach, Int. Bus. Rev. 29 (5) (2020), 101725.
[30] J. Ryan, R. Casidy, The role of brand reputation in organic food consumption: a behavioral reasoning perspective, J. Retailing Consum. Serv. 41 (2018) 239–247.
[31] M.B. Basha, D. Lal, Indian consumers' attitudes towards purchasing organically produced foods: an empirical study, J. Clean. Prod. 215 (2019) 99–111.
[32] A. Dhir, et al., Behavioral reasoning theory (BRT) perspectives on E-waste recycling and management, J. Clean. Prod. 280 (2021), 124269.
[33] A.K. Sahu, R. Padhy, A. Dhir, Envisioning the future of behavioral decision-making: a systematic literature review of behavioral reasoning theory, Australas. Mark. J. 28 (4) (2020) 145–159.
[34] S. Kushwah, A. Dhir, M. Sagar, Ethical consumption intentions and choice behavior towards organic food. Moderation role of buying and environmental concerns, J. Clean. Prod. 236 (2019), 117519.
[35] M.C. Claudy, M. Peterson, Understanding the underutilization of urban bicycle commuting: a behavioral reasoning perspective, J. Publ. Pol. Market. 33 (2) (2014) 173–187.
[36] J.M. Soon, C.J.N. Wallace, F. Science, Application of theory of planned behaviour in purchasing intention and consumption of Halal food, Nutr. Food Sci. 47 (5) (2017) 635–647.
[37] P. Salovey, J.D. Mayer, Emotional intelligence, Imagin., Cognit. Pers. 9 (3) (1990) 185–211.
[38] J. Song, H. Qu, The mediating role of consumption emotions, Int. J. Hospit. Manag. 66 (2017) 66–76.
[39] H. Han, C. Jeong, Multi-dimensions of patrons' emotional experiences in upscale restaurants and their role in loyalty formation: emotion scale improvement, Int. J. Hospit. Manag. 32 (2013) 59–70.
[40] S. Arunnaa, A.M. Safwan Marwin, The luxury value perception: Malaysian emotional intelligence towards purchase intention/Arunnaa a/p Sivapathy and Safwan Marwin Abdul Murad, Voice of Academia 17 (2) (2021) 1–10.
[41] S.F. Anderson, K. Kelley, S.E.J.P.s. Maxwell, Sample-size planning for more accurate statistical power: a method adjusting sample effect sizes for publication bias and uncertainty, Psychol. Sci. 28 (11) (2017) 1547–1562.
[42] G. Hofstede, Culture's consequences: comparing values, behaviors, institutions, and organizations across nations, Collegiate Aviation Review 34 (2) (2016) 108–109.

[43] B. Park, H. Chang, S.S. Park, Adoption of digital devices for children education: Korean case, Telematics Inf. 38 (2019) 247–256.
[44] J.-É. Pelet, S. Ettis, K. Cowart, Optimal experience of flow enhanced by telepresence: evidence from social media use, Inf. Manag. 54 (1) (2017) 115–128.
[45] D.-H. Shin, Y.-J. Shin, Why do people play social network games? Comput. Hum. Behav. 27 (2) (2011) 852–861.
[46] K. Watchravesringkan, N. Nelson Hodges, Y.H. Kim, Exploring consumers' adoption of highly technological fashion products: the role of extrinsic and intrinsic motivational factors, J. Fash. Mark. Manag. 14 (2) (2010) 263–281.
[47] S. Jilke, Measuring technological uncertainty and technological complexity: scale development and an assessment of reliability and validity, Int. J. Innovat. Sci. 13 (3) (2021) 381–400.
[48] H. Evanschitzky, et al., Consumer trial, continuous use, and economic benefits of a retail service innovation: the case of the personal shopping assistant, J. Prod. Innovat. Manag. 32 (3) (2015) 459–475.
[49] M.L. Meuter, et al., The influence of technology anxiety on consumer use and experiences with self-service technologies, J. Bus. Res. 56 (11) (2003) 899–906.
[50] S. Osswald, et al., Predicting information technology usage in the car: towards a car technology acceptance model, in: Proceedings of the 4th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 2012.
[51] C.-S. Wong, K.S. Law, The effects of leader and follower emotional intelligence on performance and attitude: an exploratory study, Leader. Q. 13 (3) (2002) 243–274.
[52] C. Fornell, D.F. Larcker, Evaluating structural equation models with unobservable variables and measurement error, J. Market. Res. 18 (1) (1981) 39–50.
[53] L.t. Hu, P.M. Bentler, Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives, Struct. Equ. Model.: A Multidiscip. J. 6 (1) (1999) 1–55.
[54] H. Jee-Hoon, S. Hye-Ji, Understanding the travel decision-making processes of COVID-19-vaccinated South Korean travelers, Heliyon 9 (2) (2023).
[55] H. Wang, G. Zong, Relationship between employees' perceived illegitimate tasks and their work procrastination behavior: role of negative emotions and paternalistic dimensions, Heliyon 9 (4) (2023).
[56] A. Abebe, A. Assemie, Quality of work life and organizational commitment of the academic staff in Ethiopian universities, Heliyon 9 (4) (2023).
[57] C. Li, et al., Perceived transaction cost and its antecedents associated with fintech users' intention: evidence from Pakistan, Heliyon 9 (4) (2023).
[58] K. Khan, et al., Psychological Distress and Trust in University Management Among International Students during the COVID-19 Pandemic, 2021, p. 2287.
[59] J. Hair, C.M. Sarstedt, Marko, Pls-sem: indeed a silver bullet, J. Market. Theor. Pract. 19 (2) (2011) 139–152.
[60] M.M. Haq, et al., The impact of deontological and teleological variables on the intention to visit green hotel: the moderating role of trust, Heliyon 9 (4) (2023).
[61] O.H. Chi, et al., Customers' acceptance of artificially intelligent service robots: the influence of trust and culture, Int. J. Inf. Manag. 70 (2023), 102623.
[62] O. Ozdemir, et al., A critical reflection on digitalization for the hospitality and tourism industry: value implications for stakeholders, Int. J. Contemp. Hospit. Manag. (2023), https://doi.org/10.1108/IJCHM-04-2022-0535.
[63] P. Goel, et al., Consumers' adoption of artificial intelligence and robotics in hospitality and tourism sector: literature review and future research agenda, Tour. Rev. 77 (4) (2022) 1081–1096.