Acceptance of contactless technology in the hospitality industry: extending the unified theory of acceptance and use of technology 2

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Contactless service has gained popularity in the hospitality industry during the COVID-19 pandemic to ensure the safety of customers and employees. This study extends the unified theory of acceptance and use of technology 2 (UTAUT2), incorporating optimism and trust, to explore the use of contactless technology in hospitality service encounters. Importance–performance map analysis (IPMA) is applied to evaluate the performance of latent constructs and enrich the findings of PLS-SEM. This study contributes to the existing literature on hospitality service innovation and technology acceptance, and has managerial implications for service design in the context of the challenges posed by COVID-19.

Keywords: contactless service, unified theory of acceptance and use of technology 2 (UTAUT2), technology acceptance, service design, customer experience, COVID-19 pandemic

Introduction

The COVID-19 pandemic has caused fundamental and seismic changes in the hospitality industry (Hao et al., 2020). The most significant of these are customers' concerns regarding social distancing, hygiene, and safety. The new normal for the future hospitality industry has changed from "high-tech" and "high-touch" to "high-tech" and "low-touch." Thus, contactless service, a technology-enabled touchless, adaptable, and customizable automation solution, has emerged as a propitious service innovation during the pandemic (Min, 2020). By leveraging contactless technology, hospitality firms can minimize human-to-human contact and augment operations and services to add value to firms and safeguard customers (Rahimizhian & Irani, 2020). The essence of contactless service in hospitality is the use of cutting-edge technology to prevent unnecessary human-to-human contact, thus creating the safest possible service encounter for both customers and employees. Pillai et al. (2021) believe that contactless technology will bring revolutionary changes to the hospitality industry and create "Hospitality 5.0," in the post-COVID-19 era.

In this study, contactless hospitality service is defined as *a contactless and hygienic service procedure and environment developed by leveraging a combined package of self-service, robotic services, and IoT-based technology implements*. In hospitality service encounters, contactless technology involves a series of technological modules including voice control (e.g. customers can control the air conditioning and lighting in a hotel room through smart speakers), motion sensing (e.g. automatic doors in aisles, virtual buttons in elevators), mobile phone control (e.g. customers can use their mobile phone to check-in, check-out, access the hotel room, make digital payments, and scan digital menus), robotic services (e.g., customers can ask service robots to deliver food, order hotel supplies, and provide directions), thermal sensing (e.g. adjusting the AC by monitoring the room temperature), facial recognition (e.g. customers can do a face scan to check-in and pay), infrared temperature measurement (e.g. customers use self-service thermometers to measure body temperature), camera (e.g. implementing video surveillance in the public relations area of the hotel), and 5G network and Internet of Things (IoT) technology to support the entire contactless technological ecosystem (Gursoy & Chi, 2020; Hao et al., 2020; Rahimizhian & Irani, 2020).

Contactless services are not an invention of the pandemic. Most technological modules had already been explored in studies on smart hotels and self-service technology in hospitality (Rosenbaum & Wong, 2015; Wu & Cheng, 2018). In the context of COVID-19, however, hotel practitioners have rearranged different technological modules with an emphasis on their contactless features. While the hotel industry is increasingly implementing contactless services to help eliminate the health risks of COVID-19, several issues remain unaddressed in customers' acceptance of contactless technology. Some customers still prefer human warmth and personal care when staying in a hotel and are reluctant to pay for surcharges of contactless technology (Menze, 2020). Some customers believe that contactless technology complicates the hotel experience, and therefore prefer human services to contactless services (Skift, 2020). Some even speculate that the reason for incorporating contactless services in hospitality is to reduce staffing cost rather than to enhance customer experience (Ben, 2021).

Therefore, it is important to understand the underlying mechanism of contactless services to enhance the extent to which customers accept them. To the best of our knowledge, no study has explored this topic. To fill this gap in the existing literature, this study adopts the unified theory of acceptance and use of technology 2 (UTAUT2) to explore the determinants of customers' acceptance and use of contactless services based on a large-scale survey of the hotel industry in mainland China. The structural relationship among the determinants is also explored. The IPMA is applied to augment the findings of PLS-SEM by adding the performance dimension of each determinant. The findings of this research are an extension of the UTAUT2 framework and current knowledge of service innovation in hospitality. In addition, this study also sheds light on the specific service design of contactless technology and hospitality services to cope with the pandemic and cater to the new normal in the post-pandemic era.

Literature review and hypotheses development

The unified theory of acceptance and use of technology

The hospitality industry is one where technological innovation has constantly been reshaping service delivery and customer experience. As a result, several theories have emerged to explain the determinants of behavioral intention and customers' acceptance of technology. The UTAUT 2 framework was developed based on the unified theory of acceptance and use of technology (UTAUT). Venkatesh et al. (2003) developed the UTAUT to provide a unified conceptual foundation for understanding customers' acceptance of technology by bringing together the theory of reasoned action (Fishbein & Ajzen, 1977), the technology acceptance model (Davis, 1989), the motivational model (Davis et al., 1992), the theory of planned behavior (Ajzen, 1991), the decomposed theory of planned behavior (Taylor & Todd, 1995), the model of PC utilization (Thompson et al., 1991), the innovation diffusion theory (Moore & Benbasat, 1991), and the socio-cognitive theory (Compeau & Higgins, 1995). UTAUT comprises effort expectancy, performance expectancy, facilitating conditions, and social influence as the main determinants of customers' behavioral intention to accept and use technology.

Effort expectancy is defined as the extent of ease related to customers' usage of technology (Venkatesh et al., 2003). Various stakeholders can be frustrated by the complexity of technology adoption in hospitality service encounters. Therefore, the easier it is to use new technology, the more customers are ready to accept it. The concept of effort expectancy is similar to concepts such as "ease of use" from the technology acceptance model, "complexity" from the model of PC utilization, and "actual ease of use" from the innovation diffusion theory.

Performance expectancy indicates the extent to which a specific technology benefits customers in carrying out certain activities (Venkatesh et al., 2003). It is a fundamental determinant of the adoption and usage of innovative technologies. Customers tend to accept technology that helps them obtain an optimized task performance. Performance expectancy is similar to concepts such as "perceived usefulness" from the technology acceptance model and the decomposed theory of planned behavior, “extrinsic motivation” from the motivational model, “task adjustment” from the model of PC utilization, and “relative advantage” from the innovation diffusion theory.

In the context of hospitality and tourism, both effort expectancy and performance expectancy have been effective in enhancing the acceptance of technologies such as intentional and actual usage of hotel front office systems (Kim et al., 2008), hotel biometric systems (Morosan, 2012), hotel mobile applications (Kwon et al., 2013; Huang et al., 2019), hotel tablet applications (Kim, 2016), radio frequency identification (RFID), cashless payment systems (Ozturk, 2016), app-based mobile tour guides (Lai, 2015), airline web-based self-service (Lee, 2016), hotel social media networks (Dieck et al., 2017), tourism user-generated content (Assaker, 2020), and online booking technology (San Martín & Herrero, 2012). Notably, the positive impact of effect expectancy on behavioral intention is strengthened by performance expectancy (Kwon et al., 2013; Wang & Qualls, 2007). Based on the literature, the following hypotheses are proposed:

H1a: Effort expectancy positively influences customers’ behavioral intention to accept contactless technology in hotels.

H1b: Performance expectancy positively influences customers’ behavioral intention to accept contactless technology in hotels.

H1c: Effort expectancy positively influences performance expectancy.

Social influence is the degree to which customers believe in opinions that important people in their lives have regarding the adoption of certain technologies (Venkatesh et al., 2003). A supportive environment may encourage customers’ behavioral intention to accept contactless services. Social influence captures the concepts of “subjective norm” from the theory of planned behavior and the decomposed theory of planned behavior, “social factors” from the model of PC utilization, and “social image” from the innovation diffusion theory.

In hospitality and tourism studies, social influence can significantly increase customers’ acceptance of social media networks (Dieck et al., 2017), tablet apps (Kim, 2016), online booking technology (San Martín & Herrero, 2012), app-based mobile tour guides (Lai, 2015), and web-based self-service (Lee, 2016). In addition, the impact of social influence on technology acceptance and usage is strengthened by effort expectancy and performance expectancy (Dieck et al., 2017). Based on the literature, the following hypothesis is proposed:

H2: Social influence has both a direct and indirect positive influence on behavioral intention a) via effort expectancy b) via performance expectancy and c) via both effort and performance expectancy.

Facilitating conditions evaluate the extent to which customers believe that the requisite organizational and technical infrastructure exists to support the performance of technology (Venkatesh et al., 2003). Facilitating conditions are a direct determinant of technology acceptance, represented as the "perceived behavioral control" from the decomposed theory of planned behavior, "facilitating conditions" from the model of PC utilization, and "perceived compatibility" from the innovation diffusion theory. Facilitating conditions have a significant impact on the adoption of green technologies in hotels (Mejia, 2019), travelers' acceptance of app-based mobile tour guides (Lai, 2015), and online booking technology in the context of rural tourism (San Martín & Herrero, 2012). Additionally, we assume that the impact of facilitating conditions on behavioral intention is mediated by effort expectancy and performance expectancy. Based on the literature, the following hypothesis is proposed:

H3: Facilitating conditions has both a direct and indirect positive influence on behavioral intention a) via effort expectancy b) via performance expectancy and c) via both effort and performance expectancy.

The unified theory of acceptance and use of technology 2

Given that contactless service is an innovative service that entails the adoption of contactless technology, the UTAUT 2 developed by Venkatesh et al. (2012) is adopted in this study as a reference framework. It is based on the theoretical foundation of UTAUT, and integrates hedonic motivation, price value, and habit into the model.

Hedonic motivation and price value are incorporated in this study as predictors of customers' acceptance of contactless services in hotels. *Hedonic motivation* indicates a pleasant state of mind acquired from adopting new technology (Venkatesh et al., 2012). Technology may generate more innovative interactions with customers and make the service encounter more enjoyable. Therefore, hedonic motivation is an important factor in behavioral intentions. *The price* *value* is defined as the customers' perceived tradeoff between the benefits of technology and the monetary cost of adopting it (Venkatesh et al., 2012). The cost and pricing structure plays an important role in influencing customers' acceptance of technology. Customers tend to accept technological innovation with a higher price value.

In the hospitality industry, hedonic motivation and price value were often examined together in technology acceptance studies. Morosan & DeFranco (2016) found that consumers' intentions to use near field communication-based mobile payments in hotels depended highly on the pleasure or enjoyment derived from engaging with this technology. Gupta & Dogra (2017) discovered that tourists' acceptance and use of location-based travel apps increased if the perceived entertainment value and monetary value were higher. In a similar vein, Rita et al. (2018) revealed that consumers' intention to use and recommend mobile hospitality services was also explained by hedonic motivation and price value. In addition, both hedonic motivation and price value positively influence effort expectancy and performance expectancy (Bendary et al., 2018; Cho & Sagynov, 2015; Tamilmani et al., 2019). Therefore, the mediating effects of hedonic motivation and price value on the path between effort expectancy and performance expectancy are also considered. Based on the literature, the following hypotheses are proposed:

H4: Hedonic motivation has both a direct and indirect positive influence on behavioral intention a) via effort expectancy b) via performance expectancy and c) via both effort and performance expectancy.

H5: Price value has both a direct and indirect positive influence on behavioral intention a) via effort expectancy b) via performance expectancy and c) via both effort and performance expectancy.

Optimism and trust are also integrated into this study. *Optimism* refers to a positive perception of technology and the belief that the technology in question can provide customers with increased control, flexibility, and efficiency (Parasuraman & Colby, 2015). Optimism (together with innovation) is considered the driving force of technology readiness, which has a significant impact on customers' technology acceptance (Parasuraman & Colby, 2015). In hospitality service encounters, optimism can enhance the effort expectancy and performance expectancy(Walczuch et al., 2007), and thus improve the behavioral intention to adopt new technology (Sun et al., 2020). Based on the literature, the following hypothesis is proposed:

H6: Optimism has both a direct and indirect positive influence on behavioral intention a) via effort expectancy b) via performance expectancy and c) via both effort and performance expectancy.

In marketing literature, *trust* indicates "the willingness to rely on an exchange partner in whom one has confidence" (Moorman et al., 1993, p. 315). It is derived from customers' confidence in the business entity to perform well and service customers' interests in the long run (Kim et al., 2001). Trust can reassure customers having high expectations of a satisfying service experience, and is therefore deemed a catalyst for technology acceptance. Since hospitality service quality depends heavily on human warmth and personal care, the uncertainty of the service efficacy of newly developed contactless services also raises the issue of trust. Moreover, the current health risks posed by the COVID-19 pandemic also highlight the trust issue. Thus, trust plays a fundamental role in accepting contactless hospitality services.

In the hospitality industry, Kim (2016) discovered that the extent of trust (in the form of credibility) positively predicted hotel customers' acceptance of tablet apps. Dieck et al. (2017) noted that trust enhanced hotel customers' acceptance of social media networks. Notably, the causal relationship between trust and technology acceptance was strengthened by effort expectancy and performance expectancy. In the aviation industry, Lee (2016) found that trustworthiness significantly influences customers' acceptance of web-based self-service. In a study of the tourism industry, Assaker (2020) verified that trustworthiness elicited travelers' usage intention toward user-generated content technology. Moreover, Lee & Song (2013) discovered that the effect of trust on behavioral intention is mediated by effort expectancy and performance expectancy. The following hypothesis is proposed based on the literature, and the proposed model is shown in Figure 1.

H7: Trust has both a direct and indirect positive influence on behavioral intention a) via effort expectancy b) via performance expectancy and c) via both effort and performance expectancy.

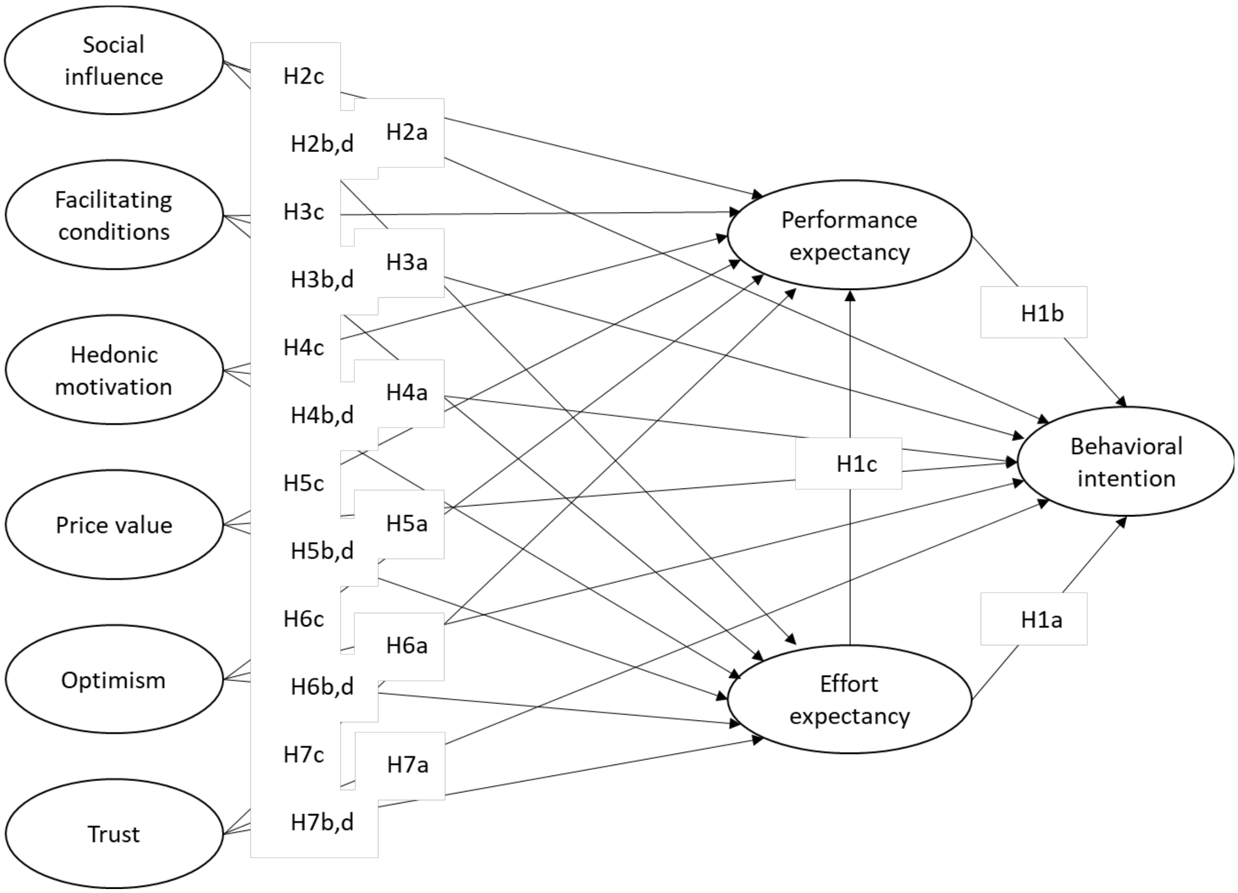

Figure 1. The proposed model of technology acceptance of contactless hospitality service

Methodology

The data were collected in China (which is referred to as the Chinese mainland in this paper) in November 2020. The study was conducted using a sample population from China since contactless technology has been widely adopted by Chinese hospitality firms (Hao et al., 2020) and it was easier for customers to understand contactless service in the hospitality industry based on their personal experiences. Data were collected through a self-reported online survey organized via a Hong Kong-based survey company. Eligible respondents were required to: 1) be adult Chinese citizens, 2) be from any of the ten selected first-tier cities, including Beijing, Shanghai, Guangzhou, Shenzhen, Chengdu, Hangzhou, Wuhan, Xi'an, Tianjin, and Qingdao, 3) have stayed at one of the thirty chosen contactless hotels recognized by major Chinese online travel agents (including Ctrip, Qunar, Mafengwo, and Fliggy) between November 2019 and November 2020.

With a combined quota sampling and random sampling method, 1800 participants were recruited from the company's 5,190,000-member-sample pool in the Chinese mainland. The company chose the sample groups according to the required balance in age, gender, and income, and subsequently applied random sampling through invitation emails. Whereas 6237 respondents participated in the survey, 1779 of them met all the requirements and completed the survey with good quality answers. The profile of the respondents is presented in Table 1.

The questionnaire took around 15-minutes to fill up. Respondents were asked to report their demographic profile, recall their last interaction with contactless technology in a contactless hotel, and to rate their experience of contactless hospitality technology on: optimism, hedonic motivation, facilitating conditions, price value, social influence, effort expectancy, performance expectancy, behavioral intention, and trust. Constructs under investigation were evaluated using a seven-point Likert scale based on existing literature. Specifically, four items of optimism were adopted by Walczuch et al. (2007), three items of hedonic motivation, four items of facilitating conditions, three items of price value, three items of social influence, four items of effort expectancy, three items of performance expectancy, and three items of behavioral intention developed by Venkatesh et al. (2012), and six items of trust developed by Gefen (2000).

Recording the sample size, Goodhue et al. (2012) argued that the rule of 10 proposed by Hair et al. (2012)—the baseline of sample size for PLS-SEM is 10 times the maximum number of indicators in one latent variable—runs a risk of a statistically significant loss of power. Therefore, a G*power test is applied to compute a desirable sample size as well. Following Faul et al. (2009), the setting 0.1 effect size, 0.01 probability of error, 0.95 power, and 8 predictors are given to an F-test with linear multiple regression for fixed model and R^2 deviation from zero in the software G*Power 3.1.9.7 version. The minimum sample size is 304 with 0.9508 actual power. Consequently, a sufficient sample size is applied in this study.

Table 1. Profile of survey participants

Items	Category	f	%	Items	Category	f	%
Gender	Male	976	54.9	Age	18–25	209	11.7
	Female	803	45.1		26–35	696	39.1
Occupation	Civil servants	350	19.7		36–45	456	25.6
	Teachers	348	19.6		46–55	158	8.9
	Business managers	279	15.7		56–65	252	14.2
	Workers	93	5.2		66 and above	8	0.4
	Farmers	172	9.7	City	Beijing	244	13.7
	Self-employed	122	6.9		Shanghai	48	2.7
	Freelancers	94	5.3		Guangzhou	944	53.1
	Full-time students	110	6.2		Shenzhen	50	2.8
	Retired	89	5.0		Chengdu	3	0.2
	Other	122	6.9		Hangzhou	130	7.3
Length of stay	1–3 nights	303	17.0		Wuhan	103	5.8
	4–10 nights	932	52.4		Xi'an	27	1.5
	11 nights and above	544	30.6		Tianjin	104	5.8
					Qingdao	126	7.1
Room price (RMB)	0–300	113	6.4	Education	Junior high and below	15	0.8
	301–600	779	43.8		High school	81	4.6
	601-900	629	35.4		Some collage	272	15.3
	901–1,200	218	12.3		Undergraduate	1296	72.8
	1,201 and above	40	2.2		Postgraduate	115	6.5
Travel companions				Monthly income (RMB)	0–3,000	3	0.2
	No travel companion	531	29.8		3,001–6,000	25	1.4
	Friends and/or relatives	324	18.2		6,001–10,000	132	7.4
	Partner	564	31.7		10,001–20,000	841	47.3
	Partner and child(ren)	354	19.9		20,001–30,000	584	32.8
	Child(ren)	6	0.3		30,001 and above	194	10.9

Data analysis and discussion

Partial least squares structural equation modeling (PLS-SEM) was adopted to analyze the data using SmartPLS 3 software. According to Hair et al. (2019), PLS-SEM has the merits of testing a theoretical framework from a predictive viewpoint or extending established theories from an exploratory perspective, testing a complex structural model that embraces many constructs, indicators, and relationships while dealing with formative constructs, financial ratios (or similar data artifacts), secondary/archival data, or a small sample size.

The current research aimed to extend the UTAUT2 framework from a predictive and exploratory perspective, and the proposed model contained nine different constructs and 27 hypotheses. Therefore, PLS-SEM is deemed more suitable. Notably, non-normal distributed data (skew = 1.8 and kurtosis = 3.8) may result in "a substantial and statistically significant loss of power" for PLS-SEM (Goodhue et al., 2012, p. 990). According to the absolute value of skewness or kurtosis of indicators in Table 2 (skew <= 1.303, kurtosis <= 2.667), this study meets the desired normalization of data for PLS-SEM (Jannoo et al., 2014).

Table 2. Descriptive statistics of indicators

Indicators	M	SD	SK	KU
EE1. Learning how to use contactless hospitality technology is easy for me.	5.610	0.981	-0.465	-0.001
EE2. My interaction with contactless hospitality technology is clear and understandable.	5.530	0.966	-0.416	-0.081
EE3. I find contactless hospitality technology easy to use.	5.560	1.007	-0.597	0.532
EE4. It is easy for me to become skillful at using contactless hospitality technology.	5.560	1.003	-0.553	0.262
PE1. I find contactless hospitality technology useful during my trip.	5.580	1.010	-0.599	0.621
PE2. Using contactless hospitality technology increases my chances of achieving things that are important to me.	5.410	1.017	-0.529	0.523
PE3. Using contactless hospitality technology helps me accomplish things more quickly.	5.550	1.015	-0.471	0.054
PE4. Using contactless hospitality technology increases my productivity.	5.510	1.014	-0.512	0.303
SI1. People who are important to me think that I should use contactless hospitality technology.	5.300	1.131	-0.628	0.628
SI2. People who influence my behavior think that I should use contactless hospitality technology.	5.270	1.121	-0.604	0.537
SI3. People whose opinions that I value prefer that I use contactless hospitality technology.	5.300	1.072	-0.680	0.804
FC1. I have the resources necessary to use contactless hospitality technology.	5.360	1.095	-0.599	0.525
FC2. I have the knowledge necessary to use contactless hospitality technology.	5.480	1.053	-0.705	0.928
FC3. Contactless hospitality technology is compatible with other technologies I use.	5.450	0.999	-0.535	0.572
FC4. I can get help from others when I have difficulties using contactless hospitality technology.	5.410	1.029	-0.651	0.913

HM1. Using contactless hospitality technology is fun.	5.530	1.049	-0.738	1.010
HM2. Using contactless hospitality technology is enjoyable.	5.540	1.054	-0.676	0.845
HM3. Using contactless hospitality technology is very entertaining.	5.620	1.029	-0.807	1.194
PV1. Contactless hospitality technology is reasonably priced.	5.280	1.070	-0.567	0.641
PV2. Contactless hospitality technology is a good value for the money.	5.510	1.044	-0.630	0.656
PV3. At the current price, contactless hospitality technology provides a good value.	5.430	1.074	-0.713	0.892
OPT1. New technologies contribute to a better quality of life.	5.810	0.987	-0.834	1.116
OPT2. Technology gives me more freedom of mobility.	5.710	0.985	-0.808	1.324
OPT3. Technology makes me more productive in my personal life.	5.820	0.991	-0.689	0.398
TR1. I believe that contactless hospitality technology is trustworthy.	5.570	1.011	-0.600	0.574
TR2. I trust in contactless hospitality technology.	5.520	1.033	-0.602	0.393
TR3. I do not doubt the honesty of contactless hospitality technology.	5.300	1.111	-0.690	0.753
TR4. I feel assured that legal and technological structures adequately protect me from problems with contactless hospitality technology.	5.390	1.100	-0.667	0.647
TR5. Even if not monitored, I would trust contactless hospitality technology to do the job right.	5.370	1.073	-0.721	0.891
BI1. I intend to continue using contactless hospitality technology in the future.	5.630	1.001	-0.653	0.771
BI2. I will always try to use contactless hospitality technology during my trip.	5.490	1.043	-0.703	0.895
BI3. I plan to continue to use contactless hospitality technology frequently.	5.470	1.063	-0.645	0.627

Note. M = Mean; SD = Standard deviation; SK = Skewness; KU = Kurtosis; EE = Effort expectancy; PE = Performance expectancy; FC = Facilitating conditions; HM = Hedonic motivation; OPT = Optimism; PV = Price value; SI = Social influence; TR = Trust; BI = Behavioral intention.

Assessing measurement models

Measurement models were evaluated based on item reliability, internal consistency, construct reliability, convergent validity, and discriminant validity (Dijkstra & Henseler, 2015b; Jöreskog, 1971). Except for FC4, all indicator loadings were higher than 0.708 (Table 3). Each construct explained over 50% of the indicator's variance, which indicated acceptable item reliability (Hair et al., 2019). The FC4 was kept for further analysis based on the acceptable validity and reliability of the FC in the measurement model (Rasoolimanesh et al., 2017).

The internal consistency of the constructs is evaluated based on composite reliability, Cronbach's alpha, and rho_A. According to Hair et al. (2019), Cronbach's alpha indicates the lower bound of internal consistency, the composite reliability represents the upper bound, and rho_A lies between the two bounds, thus suggesting a good representation of internal consistency. As shown in Table 4, higher values for the three indicators generally suggest stronger reliability. According to Jöreskog (1971), values between 0.60 and 0.70 are deemed "acceptable in exploratory research" and values between 0.70 and 0.90 ranged from "satisfactory to good." Therefore, price value had acceptable internal consistency, and all other constructs achieved satisfactory internal consistency.

Table 3. VIF and indicator loadings

	VIF	T	0.025	0.975	EE	PE	SI	FC	HM	PV	OPT	TR	BI
EE1	1.378	49.488	0.701	0.758	0.731								
EE2	1.367	58.106	0.725	0.775	0.751								
EE3	1.407	55.714	0.730	0.782	0.759								
EE4	1.439	54.220	0.727	0.783	0.756								
PE1	1.364	54.747	0.717	0.771		0.748							
PE2	1.364	49.224	0.708	0.765		0.736							
PE3	1.431	58.028	0.734	0.785		0.760							
PE4	1.414	52.738	0.718	0.773		0.747							
SI1	1.458	73.478	0.787	0.830			0.755						
SI2	1.419	59.355	0.760	0.813			0.813						
SI3	1.478	83.502	0.803	0.842			0.778						
FC1	1.388	54.943	0.732	0.784				0.759					
FC2	1.328	51.230	0.712	0.767				0.742					
FC3	1.330	44.630	0.699	0.764				0.733					
FC4	1.229	31.562	0.624	0.706				0.667					
HM1	1.440	56.622	0.765	0.820					0.794				
HM2	1.418	79.934	0.793	0.833					0.814				
HM3	1.426	66.620	0.779	0.826					0.803				
PV1	1.296	48.089	0.723	0.783						0.755			
PV2	1.364	74.266	0.790	0.833						0.813			
PV3	1.333	51.730	0.747	0.805						0.778			
OPT1	1.452	66.533	0.779	0.825							0.803		
OPT2	1.377	59.001	0.766	0.817							0.792		
OPT3	1.467	69.689	0.792	0.837							0.815		
TR1	1.495	56.221	0.721	0.774								0.750	
TR2	1.475	58.256	0.723	0.774								0.751	
TR3	1.461	42.404	0.691	0.756								0.726	
TR4	1.379	37.302	0.660	0.735								0.699	
TR5	1.402	44.150	0.675	0.736								0.707	
BI1	1.395	62.811	0.772	0.822									0.801
BI2	1.335	54.430	0.740	0.796									0.769
BI3	1.395	76.546	0.787	0.827									0.808

The construct reliability of the measurement model was examined by bootstrapping with 5000 subsamples (Table 3). The 95% confidence interval of the construct reliability was between 0.70 and 0.95, thus the construct reliability met the threshold recommended by Hair et al. (2019). Additionally, the convergent validity of each construct—the extent to which the construct converges to explain the variance of its indicators—was assessed by the average variance extracted (AVE). All AVE values were higher than 0.5, indicating that at least half of the variance of the indicators was explained by the construct (Table 4).

Table 4. Assessing reflective measurement models

	a	rho_A	CR	AVE	R^2	BI	EE	FC	HM	OPT	PE	PV	SI	TR
BI	0.704	0.705	0.835	0.628	0.618	**0.793**								
EE	0.740	0.741	0.837	0.561	0.577	0.649	**0.749**							
FC	0.700	0.703	0.816	0.527	N/A	0.64	0.675	**0.726**						
HM	0.726	0.728	0.845	0.646	N/A	0.658	0.622	0.617	**0.804**					
OPT	0.726	0.726	0.846	0.646	N/A	0.529	0.536	0.478	0.506	**0.804**				
PE	0.737	0.738	0.835	0.559	0.67	0.703	0.652	0.674	0.681	0.567	**0.748**			
PV	0.703	0.708	0.825	0.612	N/A	0.617	0.594	0.625	0.603	0.435	0.665	**0.782**		
SI	0.734	0.736	0.849	0.653	N/A	0.567	0.512	0.586	0.53	0.351	0.607	0.603	**0.808**	
TR	0.777	0.779	0.848	0.528	N/A	0.65	0.637	0.678	0.634	0.511	0.699	0.644	0.588	**0.727**

Note. a = Cronbach's alpha; rho_A = Joreskog's rho; CR= composite reliability; AVE = average variance extracted. Boldface values show the square roots of AVE.

Table 5. The heterotrait-monotrait (HTMT) ratio of correlations

	BI	EE	FC	HM	OPT	PE	PV	SI
BI								
EE	0.845							
FC	0.861	0.884						
HM	0.867	0.796	0.813					
OPT	0.687	0.683	0.621	0.646				
PE	0.894	0.829	0.888	0.877	0.724			
PV	0.837	0.779	0.857	0.802	0.562	0.884		
SI	0.738	0.640	0.768	0.671	0.429	0.774	0.801	
TR	0.826	0.785	0.869	0.789	0.625	0.870	0.832	0.729

Note: The HTMT ratio of correlations evaluates discriminant validity based on the multitrait-multimethod matrix. Ringle and Sarstedt (2015) perceived HTMT values lower than 0.9 as acceptable.

The discriminant validity of the measurement model was first assessed according to the instructions of Fornell and Larcker (1981); the positive square root of the AVE for each latent construct compared to the correlation with any other reflectively measured latent construct (Table 4). The shared variance for all latent constructs is smaller than the AVEs, thereby discriminant validity has been established among latent constructs. The Heterotrait-monotrait (HTMT) ratio of correlations is also employed to assess the discriminant validity of the measurement model (Table 5). No HTMT values were larger than 0.90, all latent constructs were empirically distinct from the other constructs, and sufficient discriminant validity was obtained throughout the measurement model.

Assessing structural models

To begin with, multivariate assumptions of outliers, normality, collinearity, and homoscedasticity were assessed based on cook's distance analysis (<= 0.1), skewness (<= 1) and kurtosis (<= 1.3) of latent variables, variable inflation factors (<= 3), and scatterplots of regression standardized residual and dependent variables accordingly (O'brien, 2007; Becker et al., 2015). No major issues were identified in this study. Moreover, to avoid the common method bias, the common method factor test was conducted. Firstly, the Harmon one-factor test (Podsakoff and Organ, 1986) was applied to the ten conceptually vital variables in the proposed model. A 33.328% extraction sums of squared loading indicates that the common method biases is not a major concern to this study. Secondly, following Liang et al. (2007), we transformed all indicators in latent constructs into single-indicator constructs, and connected each of them with both their substantive latent construct and a method construct. A bootstrapping with 5000 subsamples was conducted. As shown in Table 6, all squared values of substantive factor loadings are larger than squared values of method factor loadings, so the common method bias is not a likely contaminant of this study.

Table 6. Common method bias analysis

	R1	$R1^2$	T	P	R2	$R2^2$	T	P
BI1	0.425	0.181	65.108	0.000	0.000	0.000	0.012	0.990
BI2	0.412	0.170	66.097	0.000	-0.009	0.000	0.295	0.768
BI3	0.425	0.181	67.376	0.000	0.028	0.001	0.872	0.384
EE1	0.330	0.109	54.780	0.000	-0.022	0.000	0.683	0.495
EE2	0.328	0.108	50.708	0.000	-0.031	0.001	1.030	0.303
EE3	0.335	0.112	55.313	0.000	-0.054	0.003	1.750	0.080
EE4	0.341	0.116	59.083	0.000	-0.011	0.000	0.346	0.729
FC1	0.361	0.130	41.054	0.000	0.062	0.004	1.970	0.049
FC2	0.347	0.120	45.898	0.000	0.035	0.001	1.156	0.248
FC3	0.350	0.123	45.066	0.000	0.026	0.001	0.850	0.395
FC4	0.318	0.101	37.762	0.000	0.082	0.007	2.881	0.004
HM1	0.417	0.174	65.349	0.000	-0.032	0.001	1.024	0.306
HM2	0.413	0.171	65.123	0.000	0.018	0.000	0.566	0.571
HM3	0.414	0.171	77.017	0.000	0.016	0.000	0.502	0.615
OPT1	0.418	0.175	67.005	0.000	-0.067	0.004	2.124	0.034
OPT2	0.405	0.164	71.785	0.000	0.032	0.001	1.022	0.307

OPT3	0.417	0.174	63.466	0.000	0.114	0.013	3.873	0.003
OPT4	0.421	0.177	66.756	0.000	-0.068	0.005	2.145	0.032
PE1	0.329	0.108	55.070	0.000	-0.036	0.001	1.086	0.278
PE2	0.329	0.108	47.962	0.000	0.033	0.001	1.066	0.287
PE3	0.341	0.116	56.781	0.000	-0.049	0.002	1.502	0.133
PE4	0.338	0.114	51.323	0.000	0.009	0.000	0.296	0.767
PV1	0.417	0.174	63.466	0.000	0.024	0.001	0.708	0.479
PV2	0.434	0.188	58.112	0.000	-0.021	0.000	0.651	0.515
PV3	0.426	0.181	57.821	0.000	0.026	0.001	0.800	0.424
SI1	0.414	0.171	70.801	0.000	0.096	0.009	2.964	0.003
SI2	0.407	0.166	74.590	0.000	0.068	0.005	2.259	0.024
SI3	0.417	0.174	73.429	0.000	0.053	0.003	1.721	0.086
TR1	0.282	0.080	49.712	0.000	-0.078	0.006	2.644	0.008
TR2	0.279	0.078	47.939	0.000	0.056	0.003	1.750	0.080
TR3	0.279	0.078	47.528	0.000	0.063	0.004	1.862	0.063
TR4	0.266	0.071	38.572	0.000	-0.005	0.000	0.160	0.873
TR5	0.270	0.073	42.744	0.000	-0.055	0.003	1.814	0.070
Average		0.137				0.002		

Note: R1 = Substantive Factor Loading, R2 = Method Factor Loading. According to Liang et al. (2007), $R1^2$ should be larger than $R2^2$ to avoid the common method bias issue.

The PLS structural model is built upon a series of regression equations, and the R^2 value of the endogenous constructs is an important measurement of the explanatory power of the proposed model and the in-sample predictive power (Rigdon, 2012). The R^2 value lies between 0 and 1, and a higher value is associated with stronger explanatory power. Following the instruction of Hair et al. (2019), the thresholds for R^2, 0.25, 0.50, and 0.75, are deemed weak, moderate, and of substantial explanatory power respectively. In the proposed model, R^2 of BI = 0.618, R^2 of EE = 0.577, and R^2 of PE = 0.67, which indicate moderate to substantial explanatory power. Moreover, before assessing structural models, we established the configural, metric, and scalar invariance via different gender and age groups to validate that the factor structure and loadings are adequately equivalent among groups. No major issue was diagnosed and invariant models were achieved.

The standardized root mean square residual (SRMR), which is the square root of the average squared element of the residual correlation matrix, is also considered an important indicator of the model fit and was computed as follows: the SRMR value of the proposed model was 0.052, which was lower than the threshold of 0.08, as proposed by Henseler et al. (2016). The goodness of fit of the proposed model was acceptable. Additionally, the unweighted least squares discrepancy (dULS) was 1.416, and the geodesic discrepancy (dG) was 0.476. Using a two-round complete bootstrapping approach with the Bollen-Stine bootstrapping procedure, both dULS and dG were significant at 95% confidence intervals (Dijkstra & Henseler, 2015a, 2015b). Moreover, the normed fit index (NFI) of the proposed model was 0.90, which met the lower bound of the acceptable model fit (Henseler et al., 2016).

Table 7. Hypotheses test

		O	M	SD	T	P	Hypotheses
H1a	EE -> BI	0.148***	0.147	0.028	5.211	0.000	Supported
H1b	PE -> BI	0.21***	0.209	0.033	6.400	0.000	Supported
H1c	EE -> PE	0.092***	0.090	0.029	3.200	0.001	Supported
H2a	SI -> BI	0.088***	0.088	0.025	3.480	0.001	Supported
H2b	SI -> EE -> BI	0.004	0.004	0.004	1.070	0.285	Not supported
H2c	SI -> PE -> BI	0.028***	0.028	0.007	4.015	0.000	Supported
H2d	SI -> EE -> PE -> BI	0.001	0.001	0.001	0.985	0.325	Not supported
H3a	FC -> BI	0.085*	0.085	0.033	2.608	0.009	Supported
H3b	FC -> EE -> BI	0.044***	0.043	0.009	4.673	0.000	Supported
H3c	FC -> PE -> BI	0.026***	0.026	0.007	3.669	0.000	Supported
H3d	FC -> EE -> PE -> BI	0.006**	0.006	0.002	2.966	0.003	Supported
H4a	HM -> BI	0.171***	0.169	0.029	5.826	0.000	Supported
H4b	HM -> EE -> BI	0.026***	0.026	0.007	3.677	0.000	Supported
H4c	HM -> PE -> BI	0.04***	0.040	0.009	4.610	0.000	Supported
H4d	HM -> EE -> PE -> BI	0.003**	0.003	0.001	2.790	0.005	Supported
H5a	PV -> BI	0.082**	0.084	0.029	2.882	0.004	Supported
H5b	PV -> EE -> BI	0.017**	0.017	0.006	2.874	0.004	Supported
H5c	PV -> PE -> BI	0.033***	0.033	0.008	4.017	0.000	Supported
H5d	PV -> EE -> PE -> BI	0.002*	0.002	0.001	2.293	0.022	Supported
H6a	OPT -> BI	0.09***	0.091	0.023	3.893	0.000	Supported
H6b	OPT -> EE -> BI	0.025***	0.025	0.006	4.100	0.000	Supported
H6c	OPT -> PE -> BI	0.033***	0.033	0.007	4.660	0.000	Supported
H6d	OPT -> EE -> PE -> BI	0.003**	0.003	0.001	2.885	0.004	Supported
H7a	TR -> BI	0.093**	0.093	0.032	2.884	0.004	Supported
H7b	TR -> EE -> BI	0.021***	0.021	0.006	3.584	0.000	Supported
H7c	TR -> PE -> BI	0.037***	0.036	0.008	4.580	0.000	Supported
H7d	TR -> EE -> PE -> BI	0.003*	0.003	0.001	2.389	0.017	Supported

Note. 1. O = Original sample; M = Sample mean; SD = Standard deviation; T = T statistics; P = P values.
SRMR=0.052, d_ULS=1.416, d_G=0.476, Chi-Square=4117.696, NFI=0.90, rms Theta=0.118
2. ***p < 0.001 ; **p < 0.01 ; *p <0.05

As indicated by Chin (1998), bootstrapping with 5,000 subsamples was adopted to examine the proposed hypotheses (see Table 7). Hypotheses H1a and H1b were supported. Both effort expectancy and performance expectancy had a significant influence on behavioral intention. Hypotheses H1c was supported, which showed that effort expectancy positively influenced performance expectancy. Hypotheses H2a and H2c were supported, implying that social influence had both a direct positive influence on behavioral intention, and indirect influence via performance expectancy. However, paths from social influence to behavioral intention through effort expectancy and the joint effect of effort expectancy and performance expectancy were not significant. As a result, there is no statistical support for H2b and H2d, and effort expectancy failed to strengthen the causal relationship between social influence and behavioral intention. Hypotheses H3-7 were supported, which means that facilitating conditions, hedonic motivation, optimism, price value, and trust positively influence behavioral intention directly, via effort expectancy and via performance expectancy, and the joint mediating effects of effort expectancy and performance expectancy.

The importance-performance map analysis (IPMA)

Following Ringle and Sarstedt (2016), the IPMA is applied to enrich the findings of PLS-SEM by adding the performance dimension of each determinant (Table 8). Consequently, conclusions are drawn on both the importance dimension and the performance dimension, and this is crucial for prioritizing managerial implications. In terms of the importance, the performance expectancy, hedonic motivation, and effort expectancy have the highest (above average) total effect of direct or indirect paths between the predecessor construct and the target construct. Optimism, hedonic motivation, and performance expectancy have the highest (above average) performance. Taking performance expectancy (importance = 0.211, performance = 74.859) as an example, a one-unit rise in performance expectancy from 74.859 to 75.859 adds to the performance of behavior intention by 21.1%.

The adjusted importance-performance map is shown in Figure 2. The intersecting mean values of importance (vertical) and performance (horizontal) divided the coordinate plane into four quadrants. Hedonic motivation and performance expectancy are located in Quadrant I (high performance—high importance) and this indicates that they are important constructs and have been executed well. Optimism is located in Quadrant II (high performance—low importance). It is a less important construct but still executed well. The facilitating conditions, price value, social influence, and trust are located in Quadrant III (low performance—low importance) and they are less important constructs that require no extra managerial input. The effort expectancy is in Quadrant IV (low performance—high importance) and it is important yet has not been well-executed, and thus should be highly prioritized in managerial decisions.

Table 8. The importance-performance table

Predecessor constructs	Importance	Performance
EE	0.147	72.019
FC	0.085	73.305
HM	0.170	75.721
OPT	0.089	79.293
PE	0.211	74.859
PV	0.082	73.065
SI	0.089	71.015
TR	0.093	72.338
Average	0.121	73.952

Note: This table lists the relative importance and performance of constructs in explaining BI in the proposed structural model. The IPMA rescales data to compute performance scores on a scale from 0 to 100. 0 indicates the lowest performance whereas 100 indicates the highest performance.

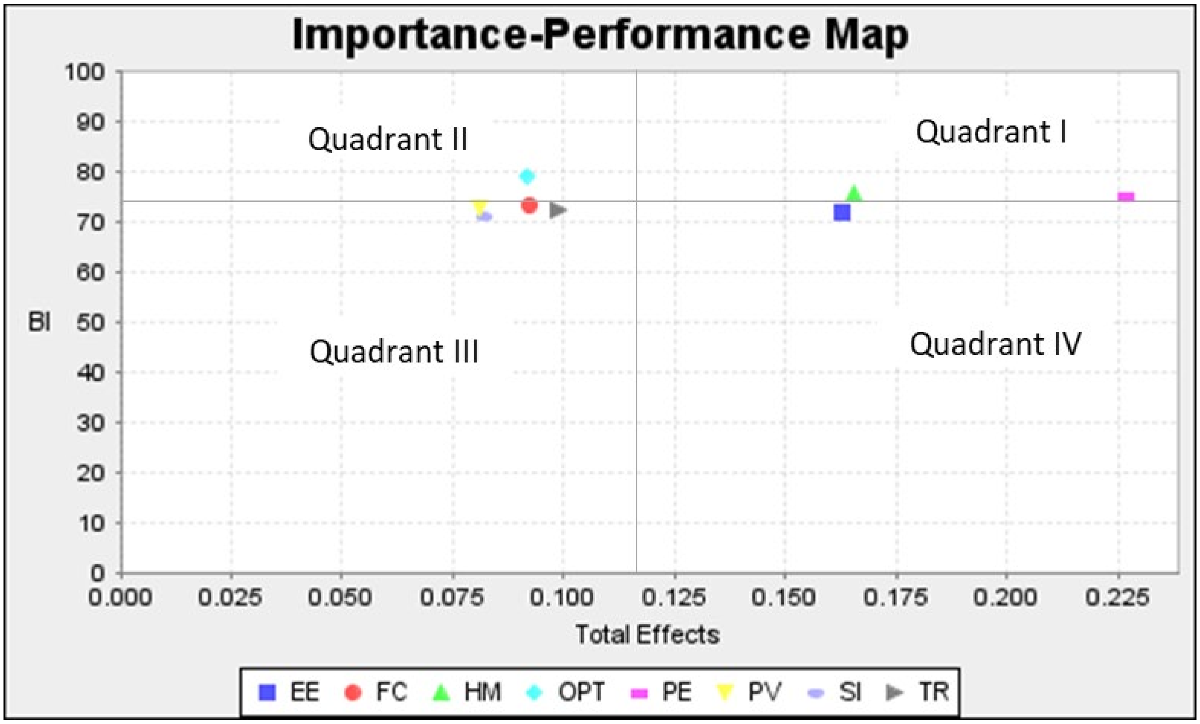

Figure 2. The importance-performance map

Conclusions and discussions

The COVID-19 pandemic has accelerated the adoption of contactless technology for hospitality service encounters, and thus it is important to understand customers' technology acceptance. This study explores how different antecedent determinants influence customers' intention to accept and use contactless technology. In line with the UTAUT (Venkatesh et al., 2003) and UTAUT2 ((Venkatesh et al., 2003; Venkatesh et al., 2012), the findings of this study indicate that effort expectancy, performance expectancy, facilitating conditions, hedonic motivation, price value, and social influence are the core determinants of customers' acceptance and usage of innovative technology.

In conformity with Sun et al. (2020), customers' optimism, as a personal characteristic, also significantly predicts their behavioral intention. Customers who are more optimistic about new technology are generally likelier to accept contactless hospitality services. Additionally, trust is an important determinant of customer behavioral intention (Assaker, 2020; Dieck et al., 2017; Kim, 2016; Lee, 2016; Park, 2020). Furthermore, the structural relationships between the different determinants were explored. Recent advancements in technology acceptance theory have identified that effort expectancy and performance expectancy mediate the influence of acceptance determinants (Blut et al., 2016; Oh et al., 2013; Sun et al., 2020). These findings indicate that effort expectancy has a significantly positive influence on performance expectancy. Customers perceived higher performance toward technology that was easier to use. Moreover, effort expectancy and performance expectancy mediate the impact of facilitating conditions, hedonic motivation, optimism, price value, and trust on behavioral intention. However, the influence of social interaction on behavioral intention is only mediated by performance expectancy.

Theoretical implications

The major theoretical contribution of this study is the extension and enrichment of the UTAUT2 framework, which is a unified theoretical foundation for technology acceptance and usage. Among the determinants of UTAUT2, performance expectancy plays the most important role in enhancing customers' technology acceptance. Functionality is the core of the service design of innovative technology. This explains why customers' acceptance of contactless technology heavily depends on pragmatism-oriented motivation. Hedonic motivation is the second most influential determinant. Customers choose to adopt a new technology not only because it is useful, but also because it is enjoyable. Trying out and interacting with new technology can create recreational experiences and increase customers' tendency to adopt the technology. Effort expectancy is the third most important determinant of technology acceptance. Customers' curiosity to try a new technology can be hampered by the complexity of technology usage. In addition, social influence, facilitating conditions, and price value also have minor impacts on customers' behavioral intention to adopt the new technology.

This study integrates optimism and trust into a technology acceptance model to depict a more holistic picture of technology acceptance. Trust is the fourth most important determinant of technology acceptance. Innovative technology generally involves risks such as privacy, cost, and service failure, and thus raises the issue of trust. In an effort to enhance customers' acceptance of contactless hospitality services, hospitality firms should strive to address customers' concerns and build customers' trust in innovative services. Optimism is integrated into the technology acceptance model to emphasize the role of customers' technology readiness on technology acceptance in the consumer setting. Although the significance of users' technology readiness and cultural values in influencing behavioral intention has been widely explored by existing studies (Parasuraman & Colby, 2015), it is largely ignored by the UTAUT2 framework. This study extends the UTAUT2 by bringing one vital dimension of technology readiness and examining its applicability in hotel service encounters. Moreover, this study explores the structural relationships between different determinants. Similar to those of Blut et al. (2016), Oh et al. (2013), and Sun et al. (2020), this study identifies the mediating effect of effort expectancy and performance expectancy on other determinants, and integrates this structural innovation into UTAUT2.

This study extends the generalizability of UTAUT2 in the context of technological innovation in the hospitality industry, especially against the current challenge of the COVID-19 pandemic, and caters to the "new normal" in the wake of the coronavirus pandemic. In an attempt to create a more secure, hygienic, effective, and pleasant service experience, contactless services have emerged to permeate various areas of the hospitality industry, including lodging, dining, airport, events, theme parks, travel, and tourism. However, studies on contactless technology mainly focus on the provider of the service (Gursoy et al., 2020; Kim et al., 2021; Min, 2020; Rahimizhian & Irani, 2020), leading to a dearth of research on contactless technology from the perspective of customers. Therefore, this study also contributes to the understanding of the underlying mechanism of acceptance of contactless technology from the viewpoint of customers.

Managerial implications

In addition to theoretical relevance, this research has managerial implications relevant to hospitality firms and provides new insight into how innovative service design can enhance customers' emotional attachment to and cognitive evaluation of hospitality brands. Since COVID-19 mainly spreads through direct or indirect close contact with infected individuals, social distancing and frequent sanitation are effective measures to halt the pandemic. Influenced by the pandemic, hospitality services will require a new approach. Customers will call for more secure—albeit engaging, effective, compelling, and memorable—experiences. Thus, contactless technology has emerged stronger during the pandemic. With more exposure to the effective, secure, and interactive experience, customers' preference for contactless services will continue in the post-pandemic era. This study provides hospitality practitioners with a precise and proactive set of determinants to improve customers' acceptance of contactless services. Contactless service can provide technology-enabled solutions to help the hospitality industry to adjust to the "new normal" and create vital changes in service provision, service design, technology implementation, management, and marketing (Pillai, Haldorai, & Kim, 2021).

Findings from IPMA shed light on the role of determinants and thus provide suggestions for effective managerial and marketing strategies (Martilla & James, 1977; Ringle & Sarstedt, 2016). In an effort to improve customers' acceptance of contactless technology, hospitality managers should prioritize improving the effort expectation of contactless technology. One of the major barriers that frustrated customers face is their concern that technology will complicate the hotel experience (Skift, 2020). Therefore, the service design of contactless technology has to be easy to use. Managers should strive to reduce the complexity of using contactless services and provide clear instructions to guide customers. They should also be prepared to assist customers through various channels when they need assistance.

The second priority of managerial actions should focus on improving the performance expectation and hedonic motivation. The service design of contactless technology should fulfill its claimed functionality. Managers should identify critical touchpoints throughout the customer journey and pinpoint the health risk and pain points within the customer journey, based on which managers can prioritize touchpoints and find the most suitable technology. The service design of contactless technology demands a comprehensive and empathetic understanding of customers (Stickdorn et al., 2018). Contactless service is not only about technology implementation but also the remodeling of products, service procedures, management operation, and customer journey with customer-oriented thinking. In doing so, the service provider can create a fully functional, smooth, and seamless experience across a holistic service cycle.

In addition, since hedonic motivation is an important determinant of technology acceptance, hospitality practitioners should explore ways to make contactless technology more enjoyable by creating more interactive, innovative, humorous, and recreational experiences. For example, during the hotel stay, contactless technology can be used to play soothing music and use aroma to create a more relaxing experience. In addition, hotels can utilize VR equipment and implement entertainment systems to delight customers.

Most importantly, hospitality practitioners should build trust with their customers. They should clearly assert that the purpose of contactless service is to secure customers and provide better services. Managers are encouraged to have open discussions with customers to understand their concerns (e.g., service quality, privacy, ethics, experience), such that it enables them to effectively address customers' concerns. Remarkably, "contactless" does not mean "service-less;" therefore, practitioners should guarantee customers sufficient human warmth and customized personal care. Notably, customers' technology readiness plays an important role in technology acceptance, and the implementation of contactless services should depend on hotels' target markets.

Particularly, hotels targeting technophilia in consumer market segmentation can embrace more revolutionary and innovative contactless elements (e.g., robotic services and smart rooms), whereas hotels targeting technophobia can be more conservative in choosing contactless elements (e.g., contactless elevator, non-contact temperature measurement).

Limitations and future research

This study has several limitations that should be considered in future studies. First, this study was conducted with data from the Chinese hospitality industry. To enhance research generalizability, future studies should test the extended UTAUT2 model in various cultural settings and service encounters. Second, the findings of this study are drawn from large-scale surveys and PLS modeling. Future studies are expected to integrate other research methods, such as service design workshops, value-adding analysis (Hao & Xiao, 2021), and experimental design. Third, cross-cultural longitudinal studies are encouraged to understand customers' acceptance of contactless technology at different developmental stages of the pandemic. Fourth, technology acceptance is measured based on behavioral intention; however, the actual usage of contactless services not only depends on customers' intentions, but equally on the availability of the technological module. Therefore, when contactless services are more widely adopted in the future, it would be meaningful to investigate the influence of behavioral intention and actual behavior on the financial performance of hospitality firms.

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