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THE MYTH OF CONTACTLESS HOSPITALITY SERVICE:

CUSTOMERS' WILLINGNESS TO PAY

ABSTRACT

Contactless hospitality services are an expensive endeavor with an uncertain return on investment. This study explores these services from the perspective of hotel guests' willingness to pay (WTP). To this end, 10 discrete choice experiments were conducted on 1,939 Chinese hotel guests to test a hybrid choice model. The findings indicate that hotel guests' WTP is influenced by hotel attributes, hotel scale, customer demographics, travel-related variables, technology readiness, and health concerns. Generally, there is significant heterogeneity in the WTP for different contactless amenities, such as for contactless room entrance, contactless payment system, contactless elevator service, robotic services, a smart room and contactless front desk services. This study contributes to the knowledge on technology implementation in the hospitality industry and the WTP for hotel amenities. Furthermore, it guides hotel practitioners to invest smartly and rationally in contactless services.

Keywords: contactless service; willingness to pay; hybrid choice model; technology readiness; COVID-19

HIGHLIGHTS

- Customers' WTP for different hotel contactless service modules is investigated
- Technology readiness and health concerns also influence WTP
- There are heterogenous WTP across contactless amenities and consumer groups
- Customized contactless service packages are recommended for different segments

INTRODUCTION

One of the most significant changes in the hospitality industry brought about by the COVID-19 pandemic is represented by customers' increased concerns for social distance, hygiene, health, and sustainability (Hao et al., 2020). These renewed expectations are likely to continue in the post-pandemic period and become the new normal. As the hospitality industry started to recover in some regions, hospitality practitioners have to implement new standard operating measures and develop innovative service technologies to adjust to this new normal. The COVID-19 pandemic has hastened the penetration of contactless technologies into the hospitality sector (Gursoy & Chi, 2020; Hao et al., 2020; Hao & Chon, 2021). According to health guidelines issued by the World Health Organization, the entire hospitality industry must re-evaluate its existing service modules and develop contactless solutions to safeguard travelers (Skift and Oracle Hospitality, 2020). Consequently, contactless service is being widely adopted by the hotel industry as a measure to minimize COVID-19 transmission and provide the safest possible experience while maintaining good service quality (Min, 2020).

Contactless service is defined as a technology-enabled "contactless and fully disinfected service procedure and environment using a combined package of self-service, robotic services, and internet of things (IoT)-based implements" (Hao and Chon, 2021, p. 2). By reorganizing existing contactless technologies around the customer journey, contactless service covers the major issues in hospitality service encounters, such as disinfection of public facilities and spaces, auto-detection of body temperature, keyless access, touchless smart rooms, and robotic services. For example, Hilton Worldwide announced the Hilton CleanStay program in May 2020 to augment contactless functionality by adding keyless room access through the Hilton Honors App, which has been applied to more than 4,800 Hilton properties across 48 countries (Hotel News Now, 2020). During the pandemic, leading Chinese hotels, including JinJiang International Holdings, Huazhu Hotels Group, Dossen International Group, Qingdao

Sunmei Group, New Century Hotels & Resorts, BTG Homeinn Hotel Group, Wanda Hotels & Resorts, and Jinling Hotel, have rolled out contactless elements in their service encounters (All-China Federation of Industry and Commerce, 2020; Hao et al., 2020).

Contactless service permeates the hotel industry and leads to fundamental changes in service provision, operational management, and marketing strategies (Jack, 2020). The hotel industry embraces contactless service to meet customers' increased demand for hygiene, cleanliness, and safety protocols via contactless check-ins, housekeeping services, ultraviolet light technology, and electrostatic spraying devices (Chen et al., 2021; Cheung et al., 2021; Pillai et al., 2021). Customers' acceptance of contactless service is determined by effort expectancy, performance expectancy, facilitating conditions, hedonic motivation, and price value (Hao, 2021). The implementation of contactless amenities is assumed to generate more delightful and higher quality experiences; adds value to customers' evaluation of the service, brand, and relationship with the hotel; and enhances customer satisfaction and trust (Hao & Chon, 2021).

However, contactless hospitality service is expensive and has uncertain returns on investment (Menze, 2020). For instance, some customers will be reluctant to pay the surcharges for contactless service because they prefer personal service and human interaction (Menze, 2020), while others might refuse to pay higher out-of-pocket expenses for contactless amenities because of the unnecessary complexity and deprived service efficiency (Skift and Oracle Hospitality, 2020). Some customers believe that contactless technological implementation reduces the cost of hotel operation and management, thus expecting that they should be charged less (Ben, 2021). Therefore, customers' willingness to pay (WTP) for contactless service is still unclear in the hospitality industry (Hotel News Now, 2020), with few studies investigating it. Further, Hao and Chon (2021) called for future studies to explore customers' WTP for major contactless amenities.

In response to this call, this study designed a series of discrete choice experiments to capture hotel guests' WTP for 10 orthogonal experimental scenarios. Each scenario includes three hypothetical hotel room packages with different hotel contactless amenity combinations. Data obtained from discrete choice experiments are estimated using a hybrid choice model (HCM). This study thus explores the influence of hotel attributes, hotel scale, customer demographics, travel-related variables, technology readiness, and health concerns on the WTP for contactless amenities. The findings are expected to create a starting point for future studies on contactless service and the pandemic-influenced consumption behaviors in the hospitality industry. They also add to technology implementation and WTP studies in hospitality. From a methodological perspective, this study sheds light on the application of a discrete choice experiment and HCM in the hospitality and tourism fields. Further, it provides guidelines for hotel practitioners' investment in contactless service.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

WTP and Hotel Amenities

WTP indicates the maximum price a customer is willing to pay for a product or service. Hotel amenities are considered to be the most significant determinant of customers' WTP (Bilgihan, 2012; Chou & Chen, 2014; Heo & Hyun, 2015; Masiero et al., 2015; Schamel; 2012; Wong & Kim, 2012). For instance, Bilgihan (2012) examined the invariance of WTP for in-room entertainment technology amenities (i.e., video on demand, music, guest device connectivity, interactive TV systems, audio-visual games, and in-room fitness), and found that customers are reluctant to pay for most amenities except for gaming consoles. In contrast to Bilgihan (2012), Wong and Kim (2012) and Chou and Chen (2014) empirically verified that hotel room views, floor, personal toiletries, environmental cooperating behaviors, service quality, and green measures have a salient impact on WTP. Heo and Hyun (2015) found that personal care items, toiletries, electronic devices, and mini-bar items predict WTP in a luxury setting. Similarly, Masiero et al. (2015) discovered that customers' WTP is influenced by room view, hotel floor, club access, free mini-bar items, smartphones, cancelation policy, hotel location, neighborhood, and online ratings. Interestingly, robotic service also contributes to increasing the WTP in hotels (Zhong et al., 2020).

Based on Hao and Chon (2021) and Hao (2021), there are six main categories of contactless amenities in hotels: contactless front desks, contactless elevators, contactless room entrances, contactless payments, smart room devices, and robotic services; however, customers' WTP for those amenities is unknown. In particular, there is a mismatch in the supply and demand of different contactless amenities (Skift and Oracle Hospitality, 2020). While 70% of hotels consider investing in self-service check-in, keyless access, food ordering, and concierge services, customers prefer contactless payments, digital room keys, and digital messaging services most. Therefore, exploring customers' WTP for various contactless amenities is critical to guide hotels' investment decisions. Based on the literature, we hypothesize:

H1: There are significant variances in the WTP for different contactless amenities.

WTP and Hotel Scale

Additionally, customers' WTP for hotel amenities varies by hotel scale (Masiero et al., 2019; Schamel, 2012). By adopting the social identity and means-end theories, Kang et al. (2012) discovered that luxury and mid-priced hotel guests have higher WTP for green practices than economy hotel guests. Chou and Chen (2014) also emphasized that the WTP for green hotel practice is generally higher in a luxury hotel setting. Based on the literature, we posit:

H2: Hotel scale has a significant influence on the WTP for contactless amenities.

WTP and Customer Demographics

Several studies have found that customer attributes are also effective determinants of the WTP for hotels (Bilgihan, 2012; Chou & Chen, 2014; González-Rodríguez et al., 2020; Heo & Hyun, 2015; Kang et al., 2012; Masiero et al., 2015, 2019; Schamel; 2012; Tang & Lam, 2017; Wong & Kim, 2012). These attributes include customer demographics, travel-related variables, and psychological inclination (Wong & Kim, 2012). In terms of demographics, Wong and Kim (2012) discovered that senior travelers tend to pay more for better room views. However, Chou and Chen (2014) argued that younger travelers prefer to spend more on a luxury room. Heo and Hyun (2015) discovered that gender and ethnicity are closely associated with the WTP for hotel rooms. In general, Asian guests exhibit a higher WTP for luxury amenities. However, Masiero et al. (2019) argued that non-Chinese and mid-high-income travelers are more generous in paying for hotel amenities. Based on the literature, this study includes customers' demographics in the HCM, and hypothesizes:

H3: Customers' (a) age, (b) education, and (c) income level have significant influences on the WTP for contactless amenities.

WTP and Customers' Travel-Related Variables

Customers' travel-related variables can also affect the WTP for hotel amenities. For example, Heo and Hyun (2015) found that leisure travelers have a higher WTP for hotel rooms compared to business travelers. Interestingly, Schamel (2012) discovered that, while business travelers are generally more price-sensitive, leisure travelers are inclined to pay more for hotels closer to the city center during the weekend, but not for room amenities and services. Masiero et al. (2015) found that customers' travel motivation (i.e., business and leisure) and frequency (i.e., first time and repeat) play important roles in shaping their WTP for a variety of hotel amenities. This finding was confirmed by the follow-up study of Masiero et al. (2019).

Therefore, this study considers the influence of customers' travel-related variables on the WTP for contactless amenities and posits the following:

H4: Customers' (a) travel companions and (b) travel frequency have significant influences on their WTP for contactless amenities.

WTP and Customers' Technology Readiness

Furthermore, customers' psychological inclinations are crucial in influencing their WTP. Based on social identity theory, means-end theory, and hedonic theory, both Kang et al. (2012) and González-Rodríguez et al. (2020) discovered that customers' WTP is related to their environmental concerns. Tang and Lam (2017) verified that Generation Y's green attitude mediates the positive impacts of their extraversion and agreeableness on WTP. Similarly, using a multinomial logit model, Chou and Chen (2014) discovered that customers' environmental attitudes and green consumer behaviors are important WTP predictors. Further, Zhong et al. (2020) emphasized that customers' technology acceptance is a key determinant of the WTP for robotic services. Technology readiness, defined as the "propensity to embrace and use new technologies for accomplishing goals" (Parasuraman, 2000, p. 308) shapes customers' perception and acceptance of emerging technologies. Technology readiness is measured by the technology readiness index (TRI), a gestalt of psychological enablers and inhibitors that predict one's predisposition to accept and use technology (Lin et al., 2007). The TRI comprises four dimensions: optimism, innovativeness, discomfort, and insecurity (Parasuraman, 2000, p. 308). Optimism is the belief that technology provides individuals with more control, flexibility, and efficiency in life; innovativeness describes one's openness to embracing cutting-edge technologies; discomfort refers to the fear of losing control over to technology and being overpowered by technology; and insecurity indicates skepticism over the competency of technologies and the avoidance of their destructive consequences (Parasuraman, 2000, p. 308).

The TRI was subsequently upgraded and streamlined into a 16-item TRI 2.0 scale by Parasuraman and Colby (2015). Contactless hospitality services are enabled by a series of state-of-the-art technologies; therefore, this study proposes:

H5: Customers' technology readiness has a significant positive influence on the WTP for contactless amenities.

WTP and Customers' Health Concerns

The COVID-19 pandemic has caused fundamental changes in customers' acceptance of technology and hospitality service consumption. Due to the concerns about COVID-19, customers demand more contactless amenities and service design throughout their hospitality journey (Hao et al., 2020). Although the hotel industry used to depend heavily on human touch, against the backdrop of the COVID-19 pandemic, customers' change of preference from human service to robotic service is salient and has led to a significant increase in the WTP for contactless robotic hospitality services (Kim, et al., 2021). Hao and Chon (2021) also revealed that the implication of contactless hotel amenities creates a better customer experience and delight and increases value, brand, and relationship equity, thus improving customer satisfaction and trust in the hotel brand. Based on the literature, this study proposes that customers' health concerns about COVID-19 affect their WTP; thus, the following hypothesis is put forward:

H6: Customers' health concerns have a significant positive influence on the WTP for contactless amenities.

SURVEY DESIGN AND DATA DESCRIPTION

Questionnaire Design

This study utilizes a discrete choice experiment to elicit respondents' preferences for various contactless services. Choice models with discrete choice experiments are popular tools for conducting consumer choice analysis (Kemperman, 2021; Qiu & De Almeida, 2022). To identify the relevant attributes of contactless service in a hotel setting, interviews were conducted with hotel managers and contactless service technology providers in China from May to July 2020. Based on these interviews, six amenities of contactless service in the hotel industry were identified: contactless front desk, elevator, room entrance, payment, smart room devices, and robotic services. Together with the room-night price, these amenities constitute a hypothetical hotel room package in the choice experiment. In particular, the six amenities are set as binary variables to indicate the availability of a specific amenity in the hotel. The room-night price pivots around the room rate of the respondent's previous hotel stay. Five percentages (82%, 93%, 100%, 113%, and 122%) of the previously paid room rate are adopted for as the price attribute in the choice tasks of each respondent. Price variation percentages are set to provide a reasonable tradeoff between the room rate and the contactless services in the experiment.

Other than the seven aforementioned attributes, all other hotel and room characteristics are considered homogenous across all hypothetical alternatives. This setting guarantees that the choices of respondents depend solely on the listed attributes. For each choice task, the respondents were provided with three unlabeled alternatives—Hotel A, Hotel B, and Hotel C—and asked to choose one of the three. A sample choice task is provided in the supplementary document.

An orthogonal design with 10 choice tasks was adopted for the pilot study conducted in November 2020. The collected sample was utilized to confirm the validity of the price range and generate an efficient design for the main survey, where 10 choice tasks are selected from a large number of potential combinations (over 5.4 million) by minimizing the D-error of the experimental design. Although an efficient design requires prior knowledge of the model estimates, it provides lower standard errors in the estimation than an orthogonal design (Rose & Bliemer, 2009).

The present study adopts TRI 2.0 (Parasuraman & Colby, 2015) [1] to understand respondents' technology readiness. The scale includes four dimensions, namely optimism (OPT), innovativeness (INN), discomfort (DIS), and insecurity (INS), which can be further classified into two categories: enablers (OPT and INN) and inhibitors (DIS and INS) (Blut & Wang, 2020; Lin et al., 2007). In this study, the 16 items of TRI 2.0, using seven-point Likert scales, were implemented after the choice experiments to extract respondents' attitudinal responses to technology innovation (please refer to the supplementary document for details).

Data Collection

A professional market research company administered the main survey in December 2020. The survey targeted mainland Chinese respondents from the top 10 first-tier cities who were at least 18 years old and had a hotel stay for at least one night in 2019. The respondents were asked to express their opinions and choices in four sections of the questionnaire, where the first one asked for information on the hotel stay profiles of respondents; the second represented the choice experiment; the third asked about respondents' attitudes on technological advancements and contactless services; and the fourth collected demographic information. A total of 1,939

[1] These questions comprise the TRI 2.0, which is copyrighted by A. Parasuraman and Rockbridge Associates, Inc., 2014. The authors have obtained the written permission from Prof Parasuraman. This scale may be duplicated only with written permission from the authors.

complete responses were collected, constituting 19,390 choice observations. The descriptive statistics of the sample is provided in the supplementary document.

MODEL AND RESULTS

Hybrid Choice Model

An HCM was chosen to estimate the data obtained from the discrete choice experiment. Compared to the non-existence of preference heterogeneity in the standard multinomial choice (MNL) model and the stochastic preference heterogeneity in the mixed logit (MXL) model, the HCM captures the preference heterogeneity of the individual using a systematic approach. In particular, the HCM integrates the MNL model with individual-specific psychological constructs and jointly estimates these two model components. The experiment choice component is modeled in the same way as a MNL model. Specifically, the utility associated with alternative *a* for respondent *i* is specified as:

$$U_{i,a} = \sum_{k=1}^{K} \beta_{i,k} X_{a,k} + \beta_{i,price} P_a + \xi_{i,a},$$

where $X_{a,k}$ represents the *K* alternative attributes indicating the availability of various amenities for contactless service, P_a is the price of the alternative, $\xi_{i,a}$ is an i.i.d. extreme value error term, and $\beta_{i,k}$ and $\beta_{i,price}$ are two sets of parameters capturing the individual preference for each contactless amenity and price, respectively.

Deviating from the MXL model, where the preference parameter ($\beta_{i,k}$) is assumed to be stochastic and follows a deterministic distribution, the individual preference in the HCM is specified as a function of *M* latent values and the prior encounters of an individual with the corresponding contactless amenity:

$$\beta_{i,k} = \theta_{k,0} + \sum_{m=1}^{M} \theta_{k,m} LV_{i,m} + \theta_{k,exp} EXP_{i,k} + \varepsilon_{i,k},$$

where $LV_{i,m}$ are M latent values that determine individual preference, $EXP_{i,k}$ is the previous experience of respondent *i* encountering contactless amenity k, $\varepsilon_{i,k}$ is an i.i.d. normal error term, and $\theta_{k,m}$ and $\theta_{k,exp}$ are two sets of parameters governing the contribution of latent values and experiences toward individual preferences, respectively. Individual experience and characteristics, such as their status of COVID-19 infection, age, income, educational level, and family status, are assumed to be significant in the formulation of individual latent values:

$$LV_{i,m} = \gamma_{m,1} COV_i + \gamma_{m,2} AGE_i + \gamma_{m,3} INC_i + \gamma_{m,4} EDU_i + \gamma_{m,5} KID_i + \epsilon_{i,m},$$

where COV_i is respondent i's degree of concern regarding COVID-19 infection (where 1: least concerned and 7: very concerned); AGE_i, INC_i, and EDU_i are sets of dummy variables revealing the age group, income group, and educational level of the respondent, respectively; KID_i indicates if the travel companion of the respondent usually include kids; $\epsilon_{i,m}$ is an i.i.d. normal error term; and $\gamma_{m,\#}$s are model parameters.

In addition to the experiment choice component described above, the HCM also includes a specification of individual psychological constructs. Each respondent's latent values are not directly observable but are identifiable by the attitudinal questions listed in Table 2. Respondents are assumed to provide responses according to:

$$I_{i,q} = \begin{cases} 1 & \zeta_q LV_{i,m} \leq \tau_{q,1} \\ 2 & \tau_{q,1} < \zeta_q LV_{i,m} \leq \tau_{q,2} \\ \vdots & \vdots \\ 7 & \tau_{q,6} < \zeta_q LV_{i,m} \end{cases},$$

where $I_{i,q}$ are the observed ratings of attitudinal question q, $\tau_{q,\#}$ are the cutoff parameters that link the respondents' latent attitude with their ratings, and ζ_q are scale parameters for different attitudinal questions.

Owing to the error term assumption of the utility function, a logit link function is adopted to model the choice probabilities as follows:

$$\mathrm{P}_i\left(y_{i,a} = 1\right) = \frac{\exp\left(U_{i,a}\right)}{\sum_j \exp\left(U_{i,j}\right)},$$

with $\mathrm{P}_i\left(y_{i,a} = 1\right)$ being the probability of respondent i choosing alternative a. The likelihood function is then constructed as follows:

$$\mathcal{L} = \prod_i \int_{\epsilon_{i,m}} \left\{ \prod_a \left[\mathrm{P}_i\left(y_{i,a} = 1\right)\right]^{y_{i,a}} \right\} \cdot \mathcal{L}_{I_i} \cdot \phi\left(\epsilon_{i,m}\right) \mathrm{d}\epsilon_{i,m},$$

with

$$\mathcal{L}_{I_i} = \prod_q \left(\sum_{s=1}^{7} \left[\frac{\exp\left(\tau_{q,s} - \zeta_q LV_{i,m}\right)}{1 + \exp\left(\tau_{q,s} - \zeta_q LV_{i,m}\right)} - \frac{\exp\left(\tau_{q,s-1} - \zeta_q LV_{i,m}\right)}{1 + \exp\left(\tau_{q,s-1} - \zeta_q LV_{i,m}\right)} \right] \right).$$

The middle term in the likelihood function ($\mathcal{L}_{I_i}$) describes the likelihood of observing a certain attitudinal item response, while the third term ($\phi\left(\epsilon_{i,m}\right)$) is the density function of the error term in the latent value function. By minimizing the negative logarithm of the likelihood function, a maximum likelihood estimation of the parameter set, $\left(\theta_{k,m}, \theta_{k,EXP}, \gamma_{m,\#}, \tau_{q,\#}, \zeta_q\right)$, can be obtained to analyze the intrinsic preferences of the respondents on contactless amenities. Figure 1 demonstrates the implementation of the above equations in the HCM of the present study. The rectangular boxes represent the observable variables, whereas the ovals refer to unobservable latent values. The solid arrows indicate cause-effect relationships, dashed lines are the manifestations of latent constructs, and dash-dotted lines link the error to the valuation equation. The model parameters are displayed in the shaded areas.

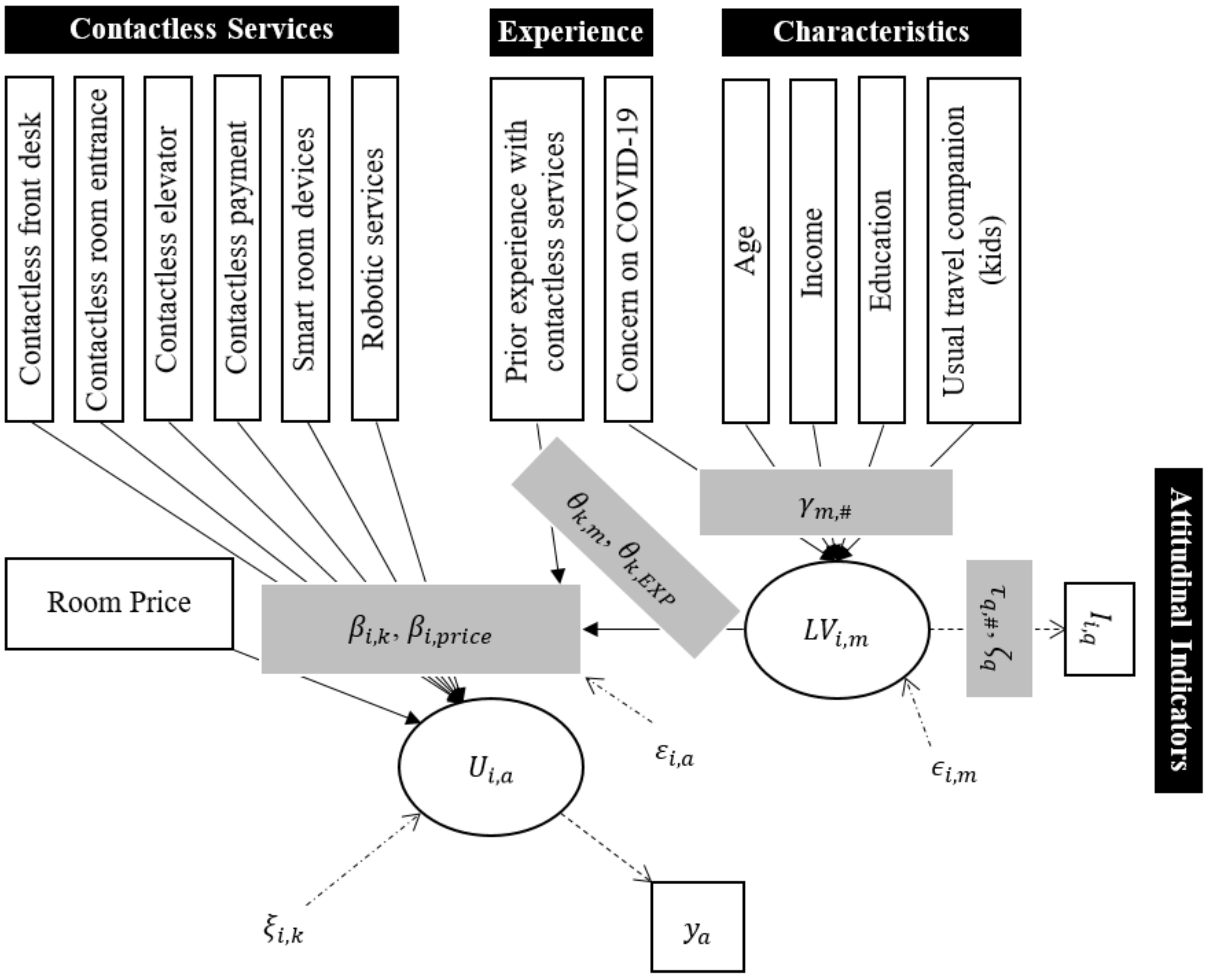
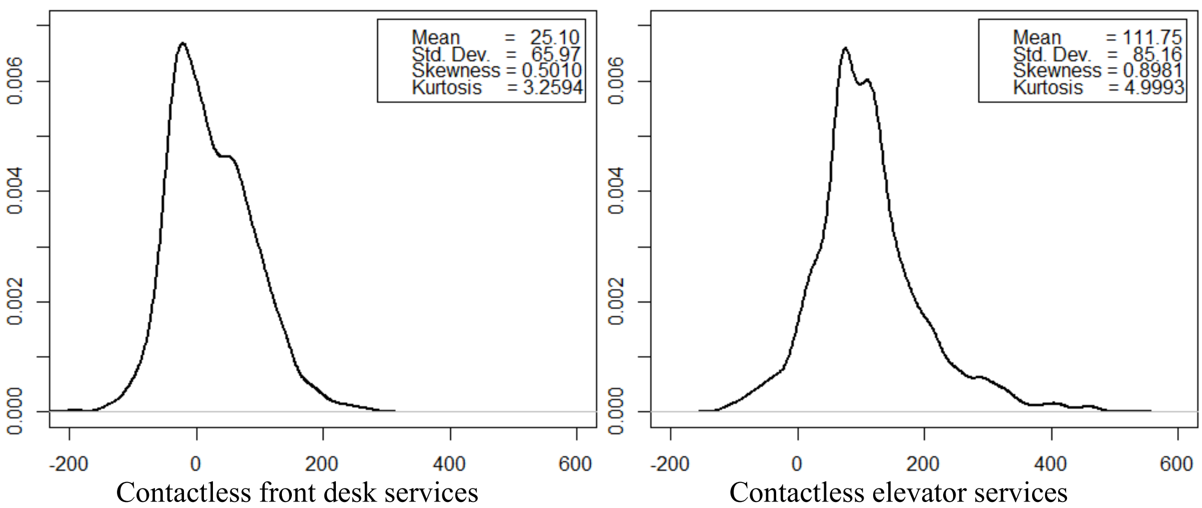


Figure 1 Path diagram of the HCM

Model Estimation and Fit

The HCM is estimated using an author-generated code based on the *Apollo* package in R (Hess & Palma, 2019a, 2019b). The coefficient on price in the utility specification ($\beta_{i,price}$) is normalized to -1 so that the estimation of the model is directly in the WTP space. The MNL and MXL models are estimated using the same sample for benchmarking purposes. The MXL model is estimated using 100 Halton draws in the simulation with all preference coefficients following normal distribution. In general, the HCM significantly outperformed its MNL and MXL counterparts. The final log-likelihood of the choices of the HCM is significantly higher at, -99,133.79, compared to -147,453.3 for the MNL and -106,377.2 for the MXL models. In terms of predictive accuracy, the MNL model can only have 37.5% of the choices correctly predicted, which is marginally better than a random guess (33.3%). The MXL model improves the predictive accuracy to 39.5%, while the HCM further boosts it to 41.8%. Both the model fit and predictive accuracy indicate the superior performance of the HCM in analyzing respondents' preferences for contactless service amenities.

The WTP for each contactless amenity ($\beta_{i,k}$) is heterogeneous across the sample by default in the HCM specification. Figure 2 shows the empirical distribution of the estimated WTP of the HCM, with the moments of each distribution presented in the legend. The horizontal and vertical axes are values of WTP and probability densities, respectively (same for empirical distributions in Figures 3 and 4). These WTP values are calculated using the model coefficients and the individual characteristics of the respondents. These estimates provide supporting evidence in favor of H1.



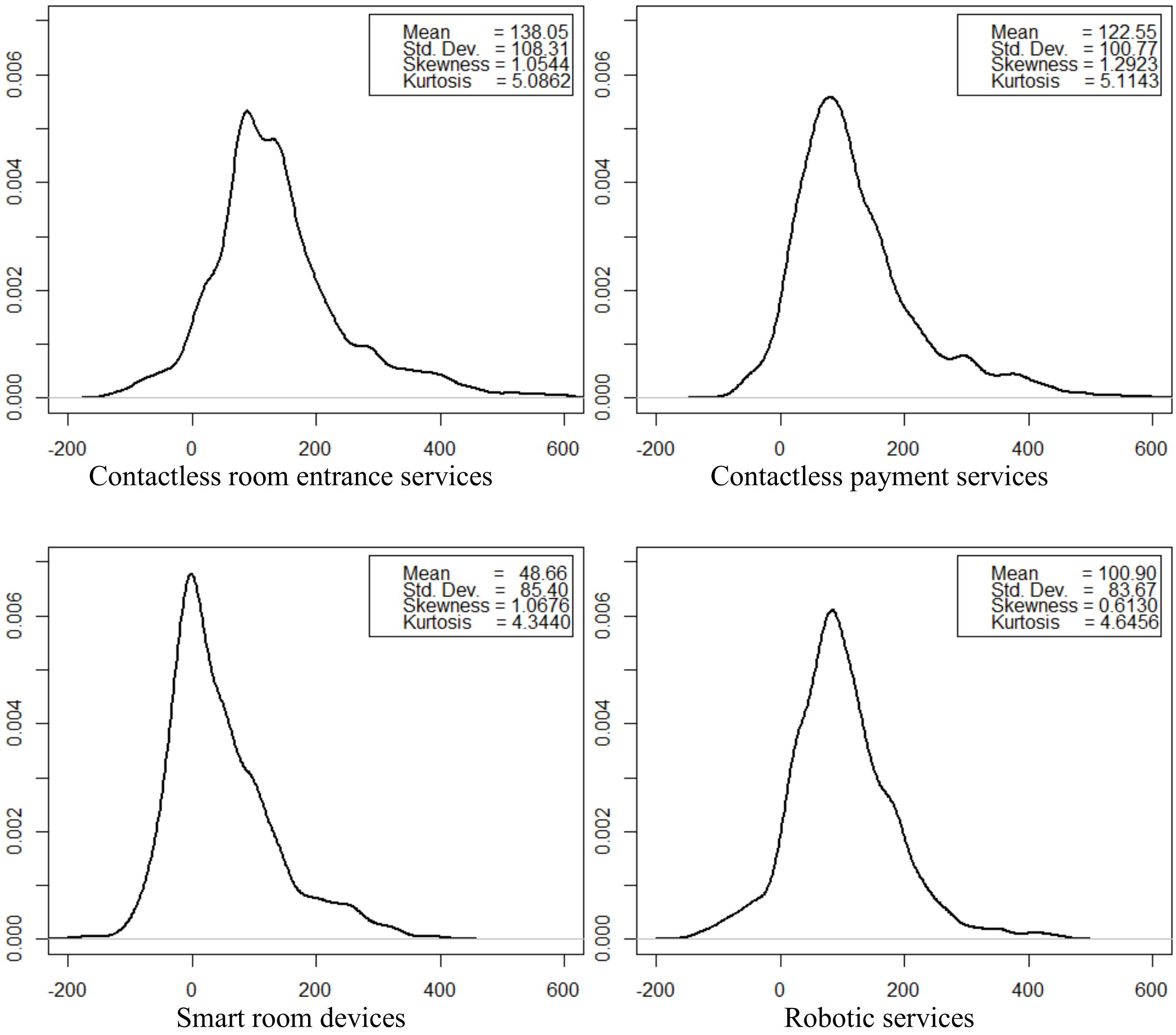


Figure 2 WTP distributions of contactless service

On average, the respondents were willing to pay ¥25.10 for contactless front desk services, ¥111.75 for contactless elevator services, ¥138.05 for contactless room entrance services, ¥122.55 for contactless payment services, ¥48.66 for smart room devices, and ¥100.90 for robotic services. Currently, China’s contactless service providers mainly focus on three amenities: contactless front desk, smart room devices, and robotic services. Interestingly, customers indicate the lowest WTP for those three amenities, whereas the highest WTP is at room entrance. This can be explained by customers’ tendency to adopt contactless services to fulfill simple and straightforward tasks (e.g., contactless room entrance, payment, and elevator services). When dealing with complex and interactive tasks, customers still prefer human assistance over contactless service. With all contactless service technologies still in the developing stage, customers may have less confidence in the machines' capability to learn the operations, and doubt the functionality and ease of use of contactless service. Therefore, they still prefer the convenience and warmth of human-to-human contact in some parts of their hotel stay. Furthermore, among all six contactless amenities, contactless front desk services require the most exposure to personal information from customers. The low WTP for this amenity could partially reflect their hesitation toward information exposure while using contactless front desk services.

Customers perceive contact with other customers as posing a higher infection risk, while contact with their travel companions and hotel staff pose lower infection risk. Therefore, they prefer to use contactless service in public spaces (e.g., contactless room entrance, contactless elevator) over those in private spaces (e.g., smart room devices) and customer-staff interaction (e.g., contactless front desk). This explains the respondents' low WTP for smart room devices (¥48.66). Considering the high investment in smart room devices in hotels, more affordable investment in contactless room entrance, payment, and elevator services could be prioritized.

Significant dispersions were observed in the distributions in Figure 2. For every contactless amenity, a small proportion of respondents had a negative WTP. These respondents would demand compensation if the corresponding contactless amenity was implemented in a hotel. These people have a strong phobia toward technological innovation and only appreciate human service during their hotel stay. The larger standard deviation of respondents' WTP for contactless service on room entrance and payment indicates a higher degree of heterogeneity within the sample for these two amenities. The positive skewness of the WTP distributions in Figure 2 fits the typical observations on WTP. A larger proportion of consumers are willing to pay a smaller amount than the few who would pay more. The high kurtosis in all distributions indicates the significant role of extreme values in generating dispersion. Specifically, with a similar standard deviation level, a larger kurtosis of the WTP for contactless elevators compared to smart room devices and robots demonstrates a larger discrepancy in respondents' opinions on contactless elevator services.

Heterogeneity of the Willingness to Pay

The estimations of γs and θs in the HCM facilitate the investigation of the heterogeneity of respondents' WTP for various amenities of contactless services. Parameter set γ describes the influence of individual characteristics on the two latent attitudinal values of the respondents on contactless service (enablers and inhibitors). Parameter set θ specifies the impact of latent attitudinal values on respondents' WTP for various contactless service amenities. Therefore, the multiplication of γ and θ not only characterizes the marginal effects of individual characteristics on respondents' WTP for various amenities of contactless services but also identifies the channel through which these influences take effect. Table 1 summarizes these marginal effects and their significance presents supporting evidence in favor of H5. The full set of estimated model parameters is provided in the supplementary document, owing to the large scale of the model (152 parameters).

The younger generation is usually assumed to be more confident with advanced technologies, yet the estimation results in Table 1 suggest a slightly higher WTP among seniors to embrace contactless services (H3a is supported). Consistent with the findings of Wang et al. (2019), senior people may not be technology-savvy, but they have a clear desire to embrace technological advancements. Respondents with a graduate level of education tend to have higher WTP for all amenities of contactless services through the inhibitor channel compared to their counterparts (H3b is supported). Nonetheless, respondents with an undergraduate or college level education are more influenced by the enabler channel. Furthermore, the respondents are not consistent across all types of contactless amenities. While they are willing to pay more for contactless front desks and robotic services, they are reluctant toward contactless payments and smart room devices. Consistent with the law of demand, respondents with higher income have a higher WTP for contactless services (H3c is supported). This increase in WTP is mainly due to the reduction in the inhibitor effect of high-tech services. Travelers with children have generally high WTP for contactless services because of the lower degree of technological inhibitors (H4a is supported). They would embrace new technologies because of the potential convenience of contactless services and the potential entertainment that contactless service could offer to their children.

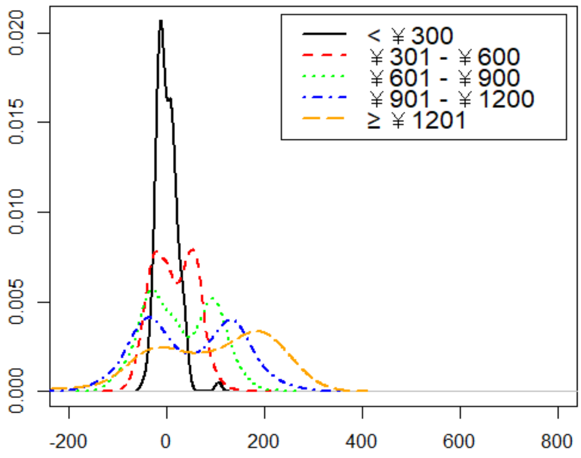
Table 1 Marginal effects of individual characteristics on WTP

Factor	*Channel*	Contactless amenities					
		Front desk	**Elevator**	**Room entrance**	**Payment**	**Smart devices**	**Robots**
Age [c]	*Enabler*	-	-	-	-	-	-
	Inhibitor	1.78	5.61	7.00	5.83	2.89	4.92
	Total	***1.78***	***5.61***	***7.00***	***5.83***	***2.89***	***4.92***
Education (university/ college)	*Enabler*	21.70	2.14	-2.99	-12.45	-23.21	15.48
	Inhibitor	- [a]	-	-	-	-	-
	Total	***21.70***	***2.14***	***-2.99***	***-12.45***	***-23.21***	***15.48***
Education (graduate)	*Enabler*	-	-	-	-	-	-
	Inhibitor	6.34	19.94	24.91	20.74	10.27	17.49
	Total	***6.34***	***19.94***	***24.91***	***20.74***	***10.27***	***17.49***
Income [b]	*Enabler*	-6.07	-0.60	0.84	3.48	6.50	-4.33
	Inhibitor	14.69	46.22	57.74	48.08	23.08	40.55
	Total	***8.61***	***45.62***	***58.57***	***51.56***	***30.29***	***36.22***
Travel with kids	*Enabler*	-	-	-	-	-	-
	Inhibitor	2.44	7.68	9.59	7.99	3.95	6.74
	Total	***2.44***	***7.68***	***9.59***	***7.99***	***3.95***	***6.74***
COVID-19 concern	*Enabler*	2.85	0.28	-0.39	1.64	-	2.03
	Inhibitor	1.21	3.82	4.77	3.98	1.97	3.35
	Total	***4.06***	***4.10***	***4.38***	***2.34***	***1.97***	***5.39***
Previous Experience		-7.66	3.41	2.59	9.10	-2.88	11.62

[a] The cells with "-" represent variables with statistically insignificant coefficients;
[b] The marginal effect of income indicates the impact of an increment of ¥3,000;
[c] The marginal effect of age indicates the impact of an increment of 10.

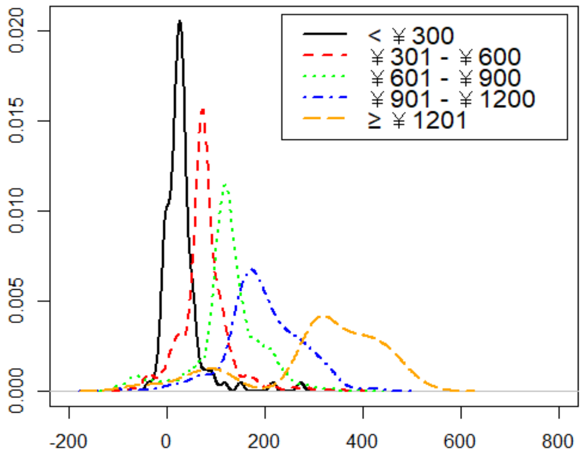
The ongoing COVID-19 pandemic has changed many aspects of our society, yet its influence on respondents' WTP for contactless services is slightly limited. While most estimations are statistically significant (H6 is statistically supported), the small marginal effects indicate insignificant economic influences. This finding can be attributed to the pandemic subsiding and the diminishing concern about COVID-19 in mainland China at the time of the data collection. The average degree of concern regarding COVID-19 infection is merely 4.95, which is slightly higher than the neutral level (4). Prior encounters with contactless service have diverse influences on respondents' WTP. Respondents who have experienced contactless elevators, room entrance, payments, and robotic services in the past tend to have a higher WTP than those new to these services. However, previous experiences reveal the opposite effect on respondents' WTP for contactless front desks and smart room devices. This finding coincides with the previous discussions that customers would expect human contact at the front desk upon their arrival at the hotel (e.g., Solnet et al., 2019).

Some interesting findings emerge from the investigation of the sample subsets. Figure 3 summarizes the group averages, the proportions of group average in the corresponding typical room rate, and the distributions of the respondents' WTP for each amenity. While considering respondents with different travel profiles, individuals who typically stay in budget hotels have a much lower WTP for all amenities of contactless services than respondents who tend to book more expensive hotels (Figure 3). This heterogeneity across customer segments provides supporting evidence in favor of H2. On average, these individuals are willing to pay a lower proportion (0.20% to 12.28%) of the price they typically pay to gain access to contactless services. By contrast, the respondents who often stay in luxury hotels are willing to pay not only a higher price but also a larger proportion (6.27% to 25.21%) to experience contactless service during their stay. Furthermore, Figure 3 presents the empirical distributions of WTP for contactless services by amenity. A clear trend of increasing average and dispersion can be observed for all contactless amenities. When the respondents pay more for a hotel stay, the intragroup preference for contactless service diversifies.



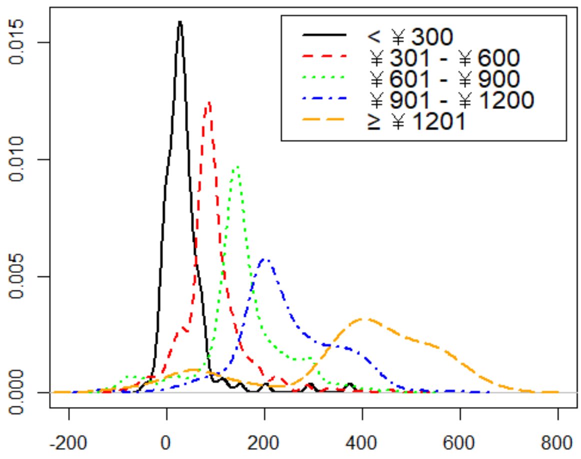
0.59	15.60	28.24	45.94	94.09
0.20%[a]	*2.60%*	*3.14%*	*3.83%*	*6.27%*
< ¥300	¥301–¥600	¥601–¥900	¥901–¥1200	≥ ¥1201

a) Contactless front desk services



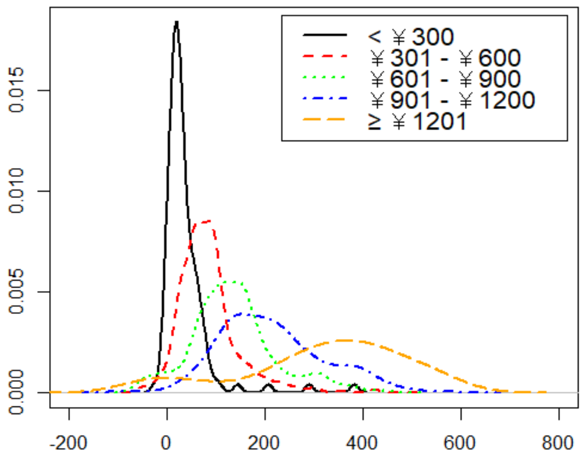
29.71	76.71	123.95	195.46	306.28
9.90%	*12.78%*	*13.77%*	*16.29%*	*20.42%*
< ¥300	¥301–¥600	¥601–¥900	¥901–¥1200	≥ ¥1201

b) Contactless elevator services



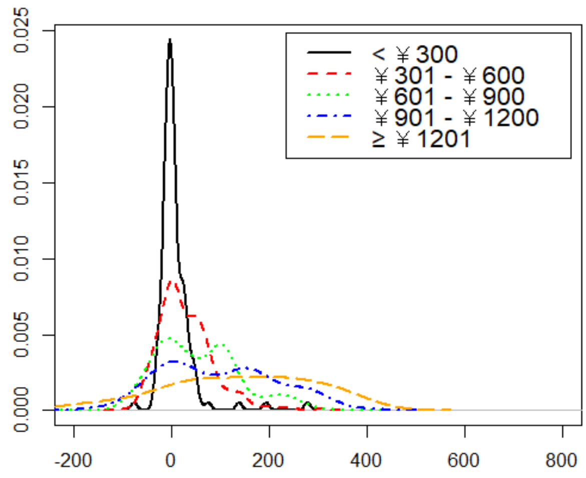
36.28	93.97	135.72	213.41	319.24
12.09%	*15.66%*	*15.08%*	*17.78%*	*21.28%*
< ¥300	¥301–¥600	¥601–¥900	¥901–¥1200	≥ ¥1201

c) Contactless room entrance services



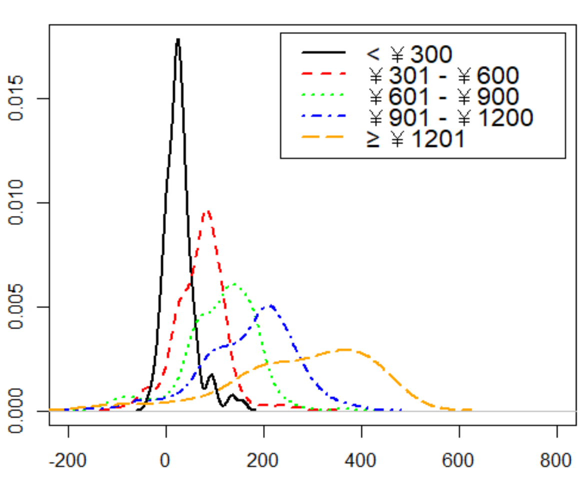
36.84	85.02	135.72	213.41	319.24
12.28%	*14.17%*	*15.08%*	*17.78%*	*21.28%*
< ¥300	¥301–¥600	¥601–¥900	¥901–¥1200	≥ ¥1201

d) Contactless payment services



8.00	29.15	55.18	97.78	137.81
2.67%	*4.86%*	*6.13%*	*8.15%*	*9.19%*
< ¥300	¥301–¥600	¥601–¥900	¥901–¥1200	≥ ¥1201

e) Smart room devices



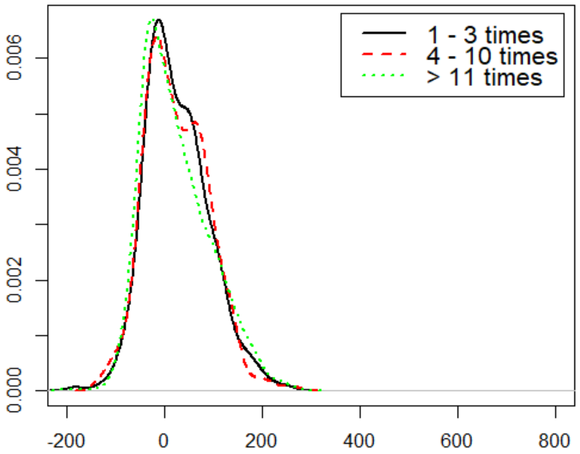
27.98	70.54	111.81	171.50	277.51
9.33%	*11.76%*	*12.42%*	*14.29%*	*18.50%*
< ¥300	¥301–¥600	¥601–¥900	¥901–¥1200	≥ ¥1201

f) Robotic services

a The percentages are calculated using the average WTP divided by the upper bound of the corresponding typical room rate interval. For group "⩾ ¥1201," a linear increment at ¥1500 is used.

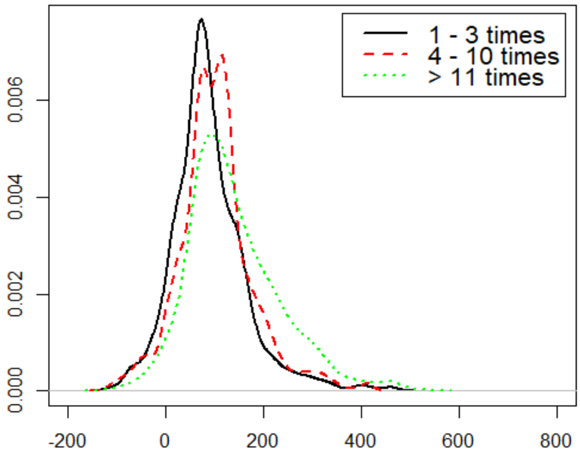
Figure 3 WTP according to the typical price of the hotel stay

Figure 4 illustrates the comparison of WTP among respondents with different frequencies of hotel stays in 2019. In general, a lower discrepancy was observed among respondents who had different travel frequencies (H4b is rejected). On average, respondents who had more than 11 hotel stay experiences were willing to pay an extra amount to experience contactless service, such as contactless elevators, room entrance, payment, smart room devices, and robotic services. Nonetheless, frequent travelers' WTP for contactless front desk service is similar to that of respondents who travel less. WTP dispersion for various amenities of contactless services is similar across respondents with different travel frequencies, with frequent travelers having a higher density on the positive end of the distribution.



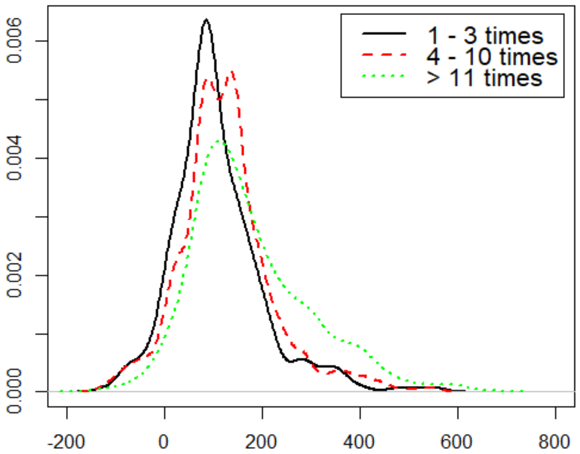
26.24	25.29	24.14
4.37%[a]	*2.81%*	*2.68%*
1-3 times	4-10 times	> 11 times

a) Contactless front desk services



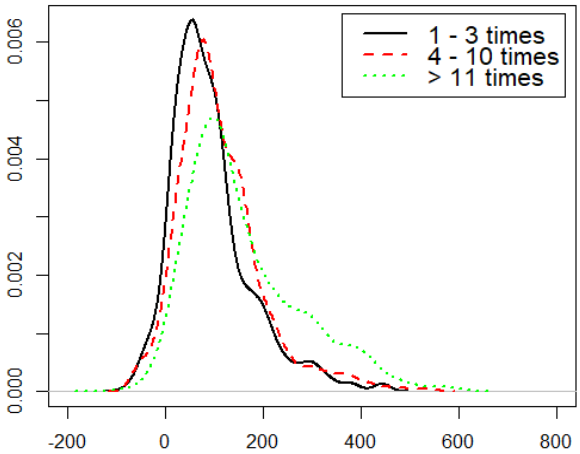
88.91	102.90	139.61
14.82%	*11.43%*	*15.51%*
1-3 times	4-10 times	> 11 times

b) Contactless elevator services



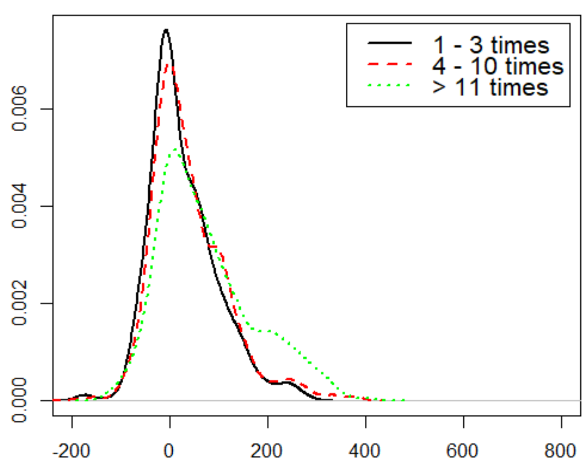
107.91	126.05	175.35
17.98%	*14.01%*	*19.48%*
1-3 times	4-10 times	> 11 times

c) Contactless room entrance services



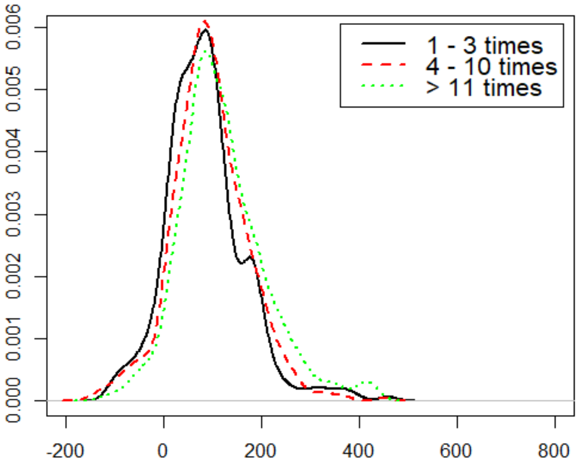
92.55	111.02	159.00
15.43%	*12.34%*	*17.67%*
1-3 times	4-10 times	> 11 times

d) Contactless payment services



28.60	40.21	74.27
4.77%	*4.47%*	*8.25%*
1-3 times	4-10 times	> 11 times

e) Smart room devices



85.43	94.67	120.16
14.24%	*10.52%*	*13.35%*
1-3 times	4-10 times	> 11 times

f) Robotic services

a The percentages are calculated using the average WTP divided by the upper bound of the median price interval of a particular category. That is, ¥600 for the "1–3 times" category; ¥900 for the "4–10 times" category; and ¥900 for the "> 11 times" category.

Figure 4 WTP according to the frequency of hotel stay

DISCUSSION AND CONCLUSIONS

This study proposes six hypotheses to identify customers' WTP for various contactless amenities in hotels and the influence of individual characteristics on heterogeneity in the WTP. The findings indicate that the WTP for hotel contactless amenities varied from ¥25.10 to ¥138.05, supporting H1. We further tested WTP heterogeneity according to the different hotel scales using respondents' typical price paid for a hotel stay, and the results support H2, showing intergroup variance in the WTP. The findings on the significant influence of customers' characteristics, including demographic, travel-related variables, and technology readiness, supports H3, H4a, and H5, but not H4b. These findings echo the existing empirical research on how customers' characteristics can affect their WTP for traditional hotel amenities (Masiero et al., 2019; Wong & Kim, 2012), and we extend their validity to new types of hotel amenities—contactless service. Regarding the impact of customers' health concerns on the WTP for contactless amenities, our findings show the statistically significant impact of COVID-19; thus, H6 is supported. However, more importantly, health concerns produced only small marginal effects.

In conclusion, this study identified preferences for hotel contactless service from the demand side and its influencing factors. Specifically, it categorized contactless service into six amenities and identified the dispersed WTP values of Chinese hotel customers using a discrete choice experiment and HCM. Using WTP as a robust measure of consumers' values and an antecedent of their purchasing behaviors (Qiu et al., 2020), we compared hotel guests' WTP for each contactless amenity. Notably, contactless service is not to everyone's taste, although the shifting balance of human versus technology encounters in service delivery brings new interaction methods. In a turbulent environment with disruptive technologies and the COVID-19 crisis, there is a paradigm shift in the hospitality industry (Bowen & Morosan, 2018; Lee & Trimi, 2021) and the insights from this study will contribute to hospitality research and business organizations searching for innovative measures in response to the pandemic and customers' concerns.

Theoretical contributions

This study makes the following theoretical and methodological contributions to the hospitality and tourism literature.

First, this study extends the understanding of hotel guests' values on different types of contactless services by comparing six contactless amenities with significant heterogeneity. Existing studies tend to be limited in consumers' WTP for a particular type of contactless services, such as robot-delivered services (Ivanov & Webster, 2021), in-room services such as voice assistants (Fan, Lu, & Mao, 2022) or enhanced disinfection technology (Zemke, Neal, Shoemaker, & Kirsch, 2015). These studies offered some theoretical implications on the current debates such as hotel guests' WTP for technology-enabled services versus human-delivered services (e.g., Ivanov & Webster, 2021; Yoganathan, Osburg, Kunz, & Toporowski, 2021), however, their findings cannot be compared with others. Guests' different WTP values for each type of contactless amenity in hotels remains unknown. Our findings revealed the difference in guests' values for each contactless amenity, which is important to comprehend the full scale of their value perception in hotel contactless services.

Second, it identified two latent values as channels that bridge customers' characteristics and their WTP for contactless amenities. The two latent values reflect customers' technology readiness and are well indicated by the two underlying dimensions of the TRI (enablers and inhibitors). Beyond existing studies that have measured the impact of customers' technology acceptance level (low versus high) on hotel purchase intention (e.g., Zhong et al., 2020), our model incorporates TRI using the enabler and inhibitor channels for customers' WTP for each contactless amenity. Therefore, our findings can provide a more holistic view on what causes heterogeneity in customers' WTP and how technology readiness can be leveraged. This not only addresses the perceived values of hotel contactless technologies from a demand-side perspective, but also extends the current knowledge on technology readiness and the WTP for new technologies.

Third, this study represents one of the first investigations that utilize the HCM to examine hotel customers' preferences for contactless service. The HCM outperformed other models in estimating respondents' WTP and provided a richer explanation of their WTP. Specifically, it allowed us to integrate attitudinal attributes into the model and show the estimated WTP distribution. Regarding the WTP determinants, two attitudinal attributes, as well as the individual characteristics of hotel customers, including personal (i.e., age, educational level, and income) and travel profiles (i.e., travelling with children and typical price of hotel stay), were also broadly identified as determinants of their WTP for contactless service. Unlike the stated WTP, the distribution of WTP using the HCM was also demonstrated to have a different skewness of the estimated WTP for each amenity. Particularly, negative WTPs were observed in contactless front desk services and smart room devices, which means that some respondents perceived these services as “cutting costs” rather than “adding value.” Although contactless technology has progressed, more empirical studies and innovative applications to service delivery are required for technology integration in the hospitality domain. This study’s rigorous micro-econometric analysis contributed to the current hospitality and tourism knowledge encompassing contactless service delivery with technology and heterogeneous customer preferences.

Fourth, as the COVID-19 pandemic is causing unprecedented disruptions to the hospitality and tourism industry, numerous studies have addressed the impact of the pandemic on changes in both customers’ perceptions of general hotel services (Hu, Teichert, Deng, Liu, & Zhou, 2021) and technology-enabled services (Kim et al., 2021; Rahimizhian & Irani, 2021). As Zeng, Chen, and Lew (2020) indicated, hospitality and tourism, traditionally perceived as a “high-touch” industry, are turning to “high-tech” industry during the COVID-19 pandemic in response to people’s acceptance of contactless services to reduce human contact and the potential spread of the virus. Although the results of our study statistically confirmed those existing findings, its economic influences were rather negligible. This implies customers’ concerns about the COVID-19 pandemic have a positive influence on their WTP for contactless services, however, an in-depth discussion is needed to reveal its impact dynamics during (within and recovering stages) and after the pandemic, as Hu et al. (2021) also emphasized.

Managerial Implications

The potential managerial contribution of this study is manifold. Obviously, contactless technologies are regarded as a solution to enhance consumers’ trust and sustain businesses in the post-COVID-19 world (Hao, 2021; Hao et al,. 2020; Hao & Chon, 2021); however, customers' preferences for various contactless services in hotels and the relevant latent variables have not yet been investigated, despite the industrial endeavors of embracing disruptive technologies. The empirical findings of this study provide three key takeaways for hotel organizations to develop more efficient contactless service design and delivery in the future.

First, among the six amenities of hotel contactless services, contactless room entrance and payment services had the highest WTP. By contrast, the WTP for contactless front desk services and smart room devices had the lowest values. This finding echoes the importance of customers' cumulative satisfaction with their WTP (Homburg et al., 2005). Most respondents had experienced two contactless amenities, contactless room entrance (63.2%), and contactless payment (78.9%), which had the highest WTP. In contrast to the higher experiential familiarity with highly valued services, the lowest WTP items, such as contactless front desk and smart room devices, were experienced by only 46.2% and 44.9% of respondents, respectively. Robotic services were a unique case, as customers have very limited previous experience with robotic technology but generally showed favorable attitudes (Choi et al., 2020). In the short run, investments in preferred contactless services, such as contactless room entrance and payments, would help hotels boost revenue as these are considered attractive traits when travel resumes. However, in the long run, hotels need to pay more attention to improving customers' awareness of less common and less preferred contactless services. For hotel organizations that pioneer new service delivery models by introducing various contactless services, user training, as the most important post-implementation of new systems for enhancing customer acceptance (Venkatesh & Bala, 2008) and accumulating positive experiences may address the current challenges of hotel contactless service (i.e., contactless front desk and smart room devices).

Hotels can also benefit from their customers' cumulative memories and experiences by designing more delightful "moments" of contactless service delivery in the long term.

Second, our analysis of the individual characteristics of hotel customers and their attitudinal values on contactless service identified several influencing factors. Interestingly, senior customers showed a higher WTP for contactless service. Therefore, contactless service marketing for seniors can be used to reduce their technological inhibitors and improve contactless service acceptance. The heterogeneous WTP according to the typical price of previous hotel stays is another noteworthy finding. Customers who generally stay in budget hotels are less likely to pay for contactless service, whereas luxury hotel customers are willing to pay more. More efforts to balance budget hotel customers' price sensitivity with technology engagement are thus required. Our results show that hotel customers' attitudinal values for contactless service consist of technological enablers and inhibitors. This implies that customers' readiness for contactless service is determined by technology-infused services in hotels and is closely related to new technology acceptance or resistance in their everyday lives. Connecting the technologies from customers' everyday lives to hotel stays could make contactless service accessible to more people.

A paradigm shift in the value creation and delivery of contactless services will generate competitive advantages for luxury hotels. Our findings suggest that customers' needs and concerns regarding technology, such as discomfort, insecurity, performance expectancy, and trust issues, should be considered when delivering high-quality contactless service. Despite the overall higher WTP of luxury hotel customers, their WTP for contactless front desk was significantly low. Furthermore, we also found a wider WTP variation for luxury hotel customers, implying their high heterogeneity in hotel contactless service preferences. Luxury hotels can differentiate their contactless service offerings by providing multiple options to customers. For instance, contactless front desk services would not entirely eliminate the physical front desk but enlarge its spatial area. A lounge with contactless front desk services can fulfill customers' desire for embracing technology and receiving a warm welcome.

Third, the WTP for contactless services was only marginally affected by COVID-19 concerns. Hotel customers consider contactless service as a technological advancement rather than a step in a hotel's response to the pandemic. Our findings also highlighted that technology could not completely substitute human input in service encounters. Hotel organizations should establish a holistic strategy to satisfy customers' desire for interpersonal linkage and technological efficiency by designing contactless technology as an augmenter of human contact in service delivery (Solnet et al., 2019).

Limitations and suggestions for future research

This study is not without limitations. The first limitation is related to the timing of the data collection. This study's sample was collected in November 2020, when China had endured a critical period and was still recovering from the effects of the pandemic. Thus, people's WTP decisions might unconsciously be affected by COVID-19 or their confidence in the prospects of economic recovery. The findings regarding the COVID-19 impact showed statistical significance, whereas its real economic influence is doubtful. This calls for a debate on the impact of the COVID-19 pandemic on the real world, as opposed to its statistical significance. Although the pandemic has accelerated the adoption of contactless technologies by hotels, this study calls for further research about the dynamic impact of the COVID-19 pandemic on both the provision of technology-enabled services and resultant customers' evaluations in the context of the evolving pandemic. The second limitation is the lack of supply-side perceptions. When we conducted several interviews with hotel practitioners to define the six amenities of contactless service, they provided practical insights and challenges to including technologies in service delivery. Future studies could focus on hotels' viewpoint to investigate the different values of each contactless amenity in the demand and supply matrix. Third, although this study establishes a statistically significant link between customers' characteristics and their WTP for contactless amenities through technology readiness, the underlying story behind these links is limited by the scope of the study. Further studies could use a qualitative approach and interview each customer segment to identify the stories behind these estimation results.

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