Hotel services in the digital age: Heterogeneity in guests' contactless technology acceptance

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Abstract: Contactless technologies have been shown to provide smarter and safer experiences to hotel guests, yet the acceptance of such technologies is not universal among hotel guests. Taking six types of contactless technology in hotel as the empirical setting, this study aims to extend the literature of technology readiness index framework and provide insights on hotel guests' acceptance of different contactless technologies. By integrating latent classes and a hybrid feature into an ordinal logit model, our investigation identified intrinsic acceptance of contactless technology and response style as two distinct sources of heterogeneity in the observed answers to technology acceptance survey. These two sources of heterogeneity play different roles in an individual's adoption of contactless technologies and have theoretical and practical importance. To better understand guests' acceptance of new technologies, researchers and practitioners should consider these types of heterogeneities in their investigations.

Keywords: technology readiness; intrinsic acceptance; response style; contactless technology; latent class hybrid ordinal logit model

1. Introduction

With the increased concern of health and hygiene in the new normal learned from the recent global pandemic, various contactless technologies are used in tourism and hospitality to offer smarter and safer experiences. In service industries and everyday life, contactless technology is not new, and many businesses use it to improve cost-effectiveness and convenience. The contactless service uptake of information and communication technologies has been widely discussed in several areas including contactless payment solutions (Karjaluoto et al., 2020), airline and airport design and operations (Liljander et al., 2006; Serrano & Kazda, 2020), and e-passport systems (Avoine et al., 2008). This technology is also used in tourism, such as Disney's MagicBand, and in hotel industry such as robotic services and various types of remote controls, both of which have been shown to benefit the industry (Hao et al., 2022; Pan et al., 2019).

Despite its potential benefits to the industry, technological innovations may face consumer resistance, and service changes that ignore customer acceptance are often delayed or unable to penetrate the market (Laukkanen, 2016). To reduce resistance, organizations should pay attention to how well they communicate with their customers about new technology-based services and products (Liljander et al., 2006; Liu et al., 2020). Research has extensively explored consumers' decisions regarding new technologies. In the areas of information systems, marketing and consumer behaviors, and psychology, various theories and models provide a theoretical lens for understanding and predicting individuals' behavioral intentions (acceptance and usage of technology) and their antecedents. Some widely adopted examples include the series of technology acceptance model (TAM) initiated by Davis (1989), the family of unified theory of acceptance and use of technology (UTAUT) from Venkatesh and Bala (2008), and the two versions of technology readiness index (TRI) originated from Parasuraman (2000). Among other important insights discovered in these studies, recognizing consumer heterogeneity regarding their acceptance and adoption of new technology is essential for successful product and service designing and promotion (Kim et al., 2017).

In the contactless technology acceptance literature, despites its wide usage and benefits to both consumers and the industry, studies also noticed that the technology is not universally accepted by customers. For instance, in a hotel context, Hao et al. (2022) found heterogeneous consumer willingness to pay for contactless services both in terms of the types of contactless technologies and among different consumer groups. Their results imply that the gain from adopting contactless technologies in hotel industry can vary in big range depending on whether the products and strategies designed meets the heterogeneous demand in the market. Hence, it is important to further investigate and understand hotel customers' heterogeneous acceptance of contactless technologies, so that the industry can design products and promotion strategies accordingly.

Through different types of contactless technology implementing in hotels, this study intends to address the lack of empirical evidence relating to heterogeneity in hotel guests' adoption of different technologies. In the present study, we assume two sources of heterogeneity in hotel guests' observed acceptance of contactless technologies: 1) the heterogenous intrinsic acceptance that reflects the true and inner desire of the hotel guests in embracing the technology; and 2) the heterogenous ways of hotel guests in expressing their intrinsic acceptance. More specifically, we aim to investigate these two sources of heterogeneity in four stages. First, we identify how individuals' formative and situational experiences influence their technology readiness propensities regarding driver and inhibitor domains of the TRI. Second, we compare the relative importance of technology readiness drivers and inhibitors in the intrinsic acceptance of different types of contactless technologies. Third, we examine how hotel guests express their idea about contactless technologies differently in responding to market survey. In particular, we explore the heterogeneity in hotel guests' response styles in rating their acceptance of contactless technologies. This investigation of heterogenous response styles not only provides insights on our second source of contactless technology acceptance heterogeneity, but also echoes the methodological concern in treating Likert-type scale data in marketing research (Dolnicar, 2021). Fourth, we classify hotel guests into classes in terms of their heterogenous response style and examine how their formative and situational experiences influences this classification. The findings of this study can shed new lights on the hotel guests' heterogeneity in accepting contactless services and provides insights both to scholars and managers in rebuilding the hospitality sector for the new normal.

2. Literature Review and Hypotheses

2.1 Contactless technology in hospitality and tourism

Contactless services have been widely discussed in the hospitality and tourism industries, especially considering the new normal in the post-pandemic era (Hao & Chon, 2021; Kim et al., 2021). Although many contactless technologies are commonplace, the supply and demand sectors in hospitality and tourism were hesitant to integrate them because service encounter standings are often based on the "low-tech, high-touch" paradigm (Bitner et al., 2000). However, recent hospitality and tourism consumers' attitudes have been dramatically changing, and from the supply side, contactless technology has become a solution for managing risk and uncertainty (Mukherjee et al., 2021) and satisfying market needs for innovative services through new guest interaction mechanisms.

Pillai et al. (2021) have defined the changes that use contactless technology to improve customer safety in their service journeys and operational efficiency as “Hospitality 5.0.” As Hospitality 5.0 technologies become integrated into customer experiences, more research is needed to understand how these technologies affect hotel guests in terms of emotions, perceptions, and behaviors (Li & Huang, 2022). Reflecting the emerging high-touch to high-tech trend in tourism and hospitality (Zeng et al., 2020), customers’ changing attitudes toward “tech” and “touch” services should be further studied because they are shaped by factors that vary by service encounters (Hao et al., 2022). However, studies tend to focus on a particular technology (e.g., service robots) or construct (e.g., general contactless technology) rather than provide a panoptic gaze of technology-enabled contactless services, as Hao et al. (2022) have criticized. In addition, research on hotel guests’ experiences with contactless technology remains in its infancy (Chen et al., 2021). Given that guests encounter different contactless technologies throughout the hotel servicescape, such as voice control, motion detection, mobile control, robotic service, thermal detection, and face recognition (Hao & Chon, 2021), a more holistic understanding is needed of their acceptance decision processes for different contactless technologies.

2.2 Technology acceptance and readiness models

Porter and Donthu (2006) addressed that two research paradigms have been developed by focusing technology or the user (i.e., technology’s attributes or individual’s propensity). Using the first paradigm, the TAM (Davis, 1989), which was derived from the theory of planned behavior, explains individual’s technology acceptance and usage in light of perceived usefulness and ease of use (Marangunić & Granić, 2015). The UTAUT, proposed by Venkatesh and Bala (2008), is also used, and the UTAUT model explains overall use intention with four factors (performance expectancy, effort expectancy, social influence, and facilitating conditions) and four moderating variables (gender, age, experience, and voluntariness of use). Although these models have wide-ranging applications, researchers have developed extended models by incorporating other factors, referred to as the TAM2 (Venkatesh & Davis, 2000), TAM3 (Venkatesh & Bala, 2008), and UTAUT2 (Venkatesh et al., 2012), to better explain technology adoption and use in research and practice.

The second paradigm focuses on latent propensity of individual to use new technology. Unlike TAM and UTAUT within the first paradigm that focus on a particular system and might not sufficiently explain consumers' individual propensities (Lin et al., 2007), the TRI follows the second paradigm. Such system specific technology acceptance theories have a limit in addressing a certain disruptive technology (Lin, Chi, & Gursoy, 2020), therefore, the TRI, which is generated from individual differences and prior experience, is widely applied in service contexts to conceptualize customers' beliefs about technology. To understand the acceptance of disruptive technologies, it is necessary to consider individual attitudes toward technology (Lin et al., 2007), as well as previous inclinations toward technological innovations, which might reflect general attitudes and predict acceptance and use (Elliott et al., 2012; Flavián et al., 2022). For example, Flavián et al. (2022) found that overall technology readiness encouraged customers to embrace innovations such as an artificial intelligence service.

Technology readiness refers to "people's propensity to embrace and use new technologies for accomplishing goals in home life and at work" (Parasuraman, 2000, p. 308). The TRI is used to identify which factors foster or hinder tendencies to accept technology-based services (Cruz-Cárdenas et al., 2021; Elliott et al., 2012; Pham et al., 2020), and it has also been used to improve customer profiling, as the industry tailors technology offerings according to customer comfort and usage patterns (Victorino et al., 2009). Numerous studies have acknowledged that the success of adopting technology-enabled services is closely related to customer readiness levels (Lee et al., 2021; Wang et al., 2017; Yoganathan et al., 2021). In addition, Birendra and Leung (2022) have emphasized the importance of technology readiness in understanding trilateral interactions between technology, supply, and demand beyond the conventional supply and demand interactions in the tourism system.

As a measurement of consumers' psychological process regarding technology-related beliefs, technology readiness is determined by an individual's positive views of technology (optimism), self-perception as a technology pioneer (innovativeness), perceived lack of control over technology (discomfort), and distrust of technology (insecurity) (Parasuraman & Colby, 2015). Optimism and innovativeness are the *driver* domains (or motivators), which contribute to technology readiness, and discomfort and insecurity are the *inhibitor* domains, which detract from it. According to the TRI, individuals possess different combinations of technology-related traits, and the interplay between drivers and inhibitors determines their technology-related behaviors. Thus, technology readiness has been used as a predictor or additional dimension in technology acceptance models (Godoe & Johansen, 2012), and it has been shown to affect consumer perceptions and attitudes, such as technology adoption decisions and cognitive evaluations (Yoganathan et al., 2021).

2.3 Technology readiness index (TRI) and influencing factors

To introduce new technology-enabled services effectively, it is important to understand which factors affect customers' willingness to accept these new technologies (Liljander et al., 2006). Previous studies provide a baseline for understanding why certain hotel guests are more willing than others to accept contactless technologies and what makes the difference in intrinsic acceptance. First, demographics are key in influencing decisions about technology (Assaker, 2020). Laukkanen (2016) emphasized that gender and age were related to notable differences in adopting technology, and these factors could apply to other service innovations. Place of residence is another important factor. Blut and Wang (2020) conducted a meta-analysis of the impact of technology readiness on technology usage and suggested that the influence of residence (or country) on consumer behaviors should be considered. Second, research has shown that travel profiles (or travel-related characteristics) also differentiate individuals (Masiero & Qiu, 2018). Specifically, past travel and hotel stay experiences, including frequency, typical budget, and travel companions (e.g., family or single traveler), might reflect the level and pattern of travel expenditures (Jang et al., 2004) and influence attitudes toward contactless technology use during hotel stays (Hao et al., 2022). Third, perceived risk is also associated with technology readiness and acceptance. Beyond the risks of using the technology itself (such as financial, informational, or performance risks) (Lam et al., 2008), situational risks, such as the COVID-19 pandemic, can be a stimulus for accepting new technologies (Ali et al., 2020; Hao et al., 2022; Li et al., 2022). It is generally accepted that the COVID-19 pandemic has accelerated the integration of contactless technologies in hospitality and tourism services, and extensive recent empirical evidence reveals the crucial role of pandemic anxiety in explaining hotel customers' behaviors toward contactless services (Li & Huang, 2022). Nevertheless, it is also found that the impact of the pandemic on people's willingness to pay for contactless services can fade rather quickly when the pandemic situation is eased (Hao et al., 2022). Fourth, technology acceptance models theorized the effects of previous experience as individuals gain hands-on experience with new technology in everyday life (Venkatesh & Bala, 2008). Prior knowledge and experience can reflect general attitudes and predict whether individuals will adopt new technologies (Elliott et al., 2012). Prior exposure to certain type of technology may also smooth the current and future use of the same type of technology, hence increase individual's acceptance of and willingness to pay for that technology (Hao et al., 2022). In tourism studies, tourists' prior experience of technology usage is proven to be important for understanding tourists' evaluations of new technologies and is frequently adopted as a salient construct in technology acceptance models (Belarmino et al., 2021; Huang et al., 2019).

These formative and situational factors, such as demographics, travel profiles, COVID-19 concerns, and experiences, are associated differentially with technology readiness and influence the use of and attitudes toward technology (King & He, 2006; Porter & Donthu, 2006; Venkatesh et al., 2012). Based on the findings that consumer technology readiness is an indicator of predicting technology acceptance, this study proposes the following hypotheses:

H1: Hotel guests' readiness (drivers and inhibitors) for contactless technology varies by (a) gender, (b) age, (c) city of residence, (d) education level, (e) household income, (f) travel frequency, (g) hotel budget, (h) travel companion, (i) COVID-19 concerns, and (j) previous experiences.

H2: Hotel guests' intrinsic acceptance of different types of contactless technology varies according to their technology readiness propensities in terms of drivers and inhibitors.

2.4 Response style

Using questionnaires with Likert-type scales is common in marketing research (Weijters et al., 2010). However, questionnaires with bipolar ordinal scales have been debated because of response style bias and a lack of reliability (Dolnicar, 2021). Methodologically, response styles are a key cause of method bias, which can affect validity, reliability, and covariation in marketing research (MacKenzie & Podsakoff, 2012). As ordinal scales are susceptible to response style, heterogeneity in respondents' response styles is regarded as a source of contamination in questionnaire ratings (Baumgartner & Steenkamp, 2001; Greenleaf, 1992). This problem occurs because survey respondents vary greatly in the way they use rating scales (van Rosmalen et al., 2010), such as having extreme or acquiescence response styles. When an ordinal scale is coarsely designed to measure a latent continuous variable, respondents with different response styles may answer differently, even if they do not differ in values or beliefs (Grün & Dolnicar, 2016). This bias can be removed by adding questions, standardizing responses, performing robustness-based correction, and using integrated models of simultaneous data analysis and response style correction (Grün & Dolnicar, 2016).

In tourism research, methodological concerns regarding response style have been carefully discussed (Dolnicar et al., 2015). As Dolnicar (2021) indicated, respondents have styles or preferences for answering questions with 5- or 7-point Likert scale options, irrespective of the question asked, and this variation generates concern because of tourists' culture-specific response styles. In addition, response style is regarded as an indicator of data quality (Dolnicar et al., 2009), and efforts have been made to minimize biases in survey design and analysis, such as by adding extra response points (Stylos et al., 2017) and using alternative answer formats (Hajibaba et al., 2015). However, more research is required to incorporate response style into model estimation to better recognize customers' heterogeneity in values and response styles (Grün & Dolnicar, 2016; Sæþórsdóttir et al., 2022).

A typology based on individual response style has received considerable attention in consumer behavior studies (Singh, 1990). To express and communicate rational evaluations and emotions (such as satisfaction) in consumers, Singh (1990) classified response styles into *passives*, *voicers*, *irates*, and *activists*. The findings indicated that style was influenced by individual characteristics (e.g., demographics, prior experience, and service category) and further generated differences in word-of-mouth (WOM) or switch (or loyal) behaviors. Focusing on variance in response style, van Vaerenbergh and Thomas (2013) identified several types of response styles influenced by demographic and cultural variables, such as education, age, gender, income, employment, race, personality, and culture- and country-level characteristics. Ares and Jaeger (2022) have also urged that more effort be made to mitigate the effects of response style, given that consumer behavior research relies on survey methods and scaled responses.

Despite the abovementioned progress, a lack of discussion exists in hospitality and tourism studies about individual heterogeneity in rating styles. In addition, practically, response style could indicate an individual's personality characteristics and reflect the way this individual express him/herself on ideas (Hamilton, 1968). The heterogeneity in response styles therefore influences the effectiveness of WOM in the market. For example, given two individuals with same level of intrinsic acceptance of a contactless technology, the "yessaying" type individual (who has the tendency to rate positively regardless content) would deliver more positive information to others on the experience of using that technology. Accordingly, this study proposes the following hypotheses:

H3: Hotel guests' response styles to survey scales vary by (a) gender, (b) age, (c) city of residence, (d) education level, (e) household income, (f) travel frequency, (g) hotel budget, (h) travel companion, (i) COVID-19 concerns, and (j) previous experiences.

H4: Hotel guests' response styles affect observed acceptance ratings, which reflect their intrinsic acceptance.

Figure 1 presents the hypothesized relationships and conceptual framework of the study. We propose that technology readiness is a major factor influencing individual's intrinsic acceptance of contactless technology (H2), and is influenced by individual characteristics such as formative and situational experiences (H1). The way people express their opinion on the acceptance of contactless technology is determined by the intrinsic acceptance of such technology as well as their response styles (H4), which is also influenced by individual characteristics (H3).

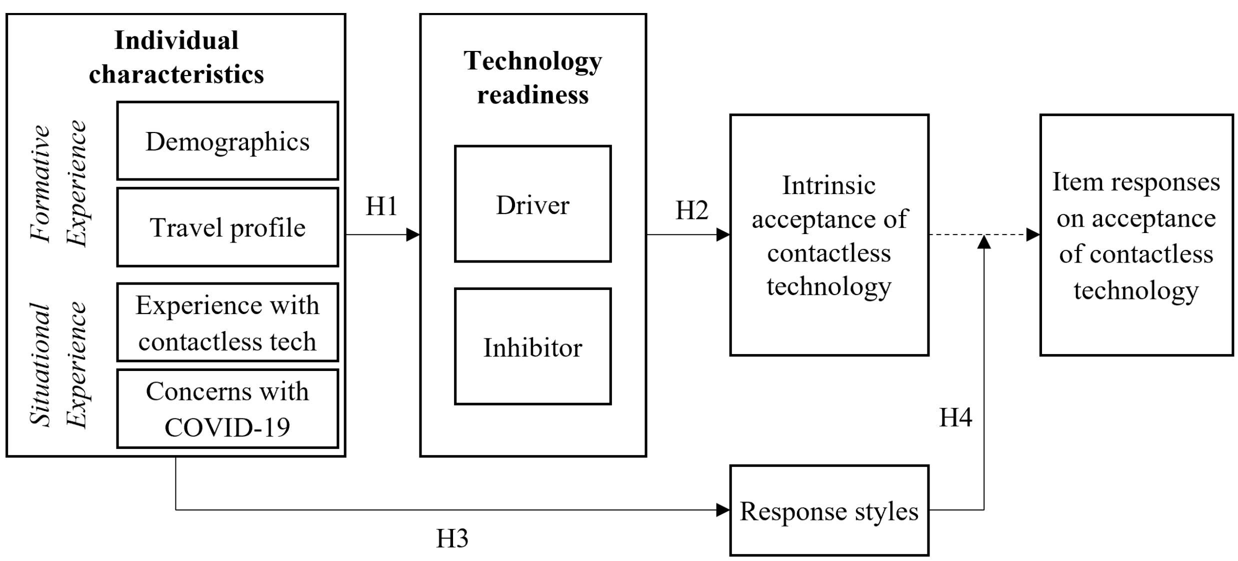

Figure 1. Conceptual framework of the study

3. Methodology

3.1 Data collection and sample description

The survey used in this study follows the typical TRI survey, including sociodemographic information, the 16 items from TRI 2.0, and respondents' acceptance ratings for six types of contactless technology, ranging from 1 (strongly oppose) to 7 (strongly accept). The survey was administered online by a professional market research company in December 2020, and it targeted adult respondents from major cities in Mainland China who had a hotel stay in 2019. Online invitations were sent throughout December 2020 and included screening questions about age and hotel stay experiences. A total of 1927 completed responses were received, and the sample statistics are presented in Table 1. As reflected in Table 1, the sample is balanced in terms of respondents' gender, age, educational background and income. Since contactless technologies are more adopted in higher-tier cities, the sample skewed towards respondents from the first-tier cities. In terms of prior experience with contactless services, most respondents (> 90%) had experienced at least one type of contactless services, with contactless payment being the most common type and the robotic services being the least common.

Table 1. Sample statistics

Variable	Count	(Frequency)	Variable	Count	(Frequency)
Gender			Frequency of hotel stay (2019)		
Female	874	(45.4%)	1–3 times	340	(17.6%)
Male	1053	(54.6%)	4–10 times	999	(51.8%)
Age			11 times and above	588	(30.5%)
18–25	199	(10.3%)	Typical price of hotel stay		
26–35	779	(40.4%)	Below ¥300	115	(6.0%)
36–45	499	(25.9%)	¥301–¥600	824	(42.8%)
46–55	173	(9.0%)	¥601–¥900	709	(36.8%)
56–65	268	(13.9%)	¥901–¥1,200	230	(11.9%)
66 and above	9	(0.5%)	¥1,201 and above	49	(2.5%)
City of residence			Typical travel companion		
First-tier cities	1146	(59.5%)	With kids	402	(20.9%)
Other cities	781	(40.5%)	Without kids	1525	(79.1%)
Educational level			Concern of COVID-19 infection (1 least-7 very)		
Below undergraduate	396	(20.6%)	Mean	4.9476	
Undergraduate and above	1531	(79.4%)	Standard deviation	1.5213	
Household income			Previous experiences with contactless services		

Below ¥10,000	172	(8.9%)	Contactless front desk	884	(46.2%)
¥10,001–¥20,000	887	(46.0%)	Contactless elevator	1005	(52.4%)
¥20,001–¥30,000	661	(34.3%)	Contactless room entrance	1213	(63.2%)
¥30,001 and above	207	(10.7%)	Contactless payment	1517	(78.9%)
			Smart room devices	859	(44.9%)
			Robotic services	627	(32.7%)

3.2 Model specification and estimation

This study adopts an ordinal logit (OL) model (McCullagh, 1980) to investigate respondents' acceptance of various types of contactless technology. The model considers the joint influences of individual intrinsic acceptance and response style on the self-reported acceptance rating obtained from our survey. In particular, following the TRI framework, individual intrinsic acceptance is driven by two dimensions, technology readiness drivers and inhibitors, which are summarized from the four subdimensions of technology readiness: optimism (OPT), innovativeness (INN), discomfort (DIS), and insecurity (INS) (Parasuraman & Colby, 2015). The drivers and inhibitors are further determined by respondents' individual characteristics, including demographics, traveling profiles, prior experiences with contactless technology, and attitudes toward technology innovation (e.g., Assaker, 2020; Cruz-Cárdenas et al., 2021; Elliott et al., 2012; Hao et al., 2022). Respondents are specified to exhibit response style heterogeneity (Bertrand & Hafner, 2014; Grün & Dolnicar, 2016; van Herk et al., 2004), with response styles influenced by sociodemographic factors (Bertrand & Hafner, 2014).

To capture the systematic heterogeneity in respondents' acceptance of contactless technologies, this study adopts the idea of the hybrid feature from the hybrid choice model (Ben-Akiva et al., 2002; Kim et al., 2014) and incorporates item responses to attitudinal questions into the estimation of the typical ordinal logit model. Response style heterogeneity is further specified by a latent class component of the model. The details of the model specification are as follows:

For each type of contactless technology, the respondents are assumed to have an intrinsic acceptance scale driven by their technology readiness drivers and inhibitors

$$S_{k,i} = \zeta_{1,l,i} DRIVER_i + \zeta_{2,k,i} INHBTR_i + \epsilon_{k,i}, \quad (1)$$

where $S_{k,i}$ is a decision scale that describes the intrinsic acceptance of respondent i of contactless technology k and governs the corresponding answer in the scale question; $DRIVER_i$ and $INHBTR_i$ are unobservable values of respondents' technology readiness drivers and inhibitors; ζs are the marginal contributions of drivers and inhibitors to the decision scale; and $\epsilon_{k,i}$ is the error term.

The probability of observing an answer of rating s in response to contactless technology k, $\mathrm{P}_{k,i}(y_{k,i} = s)$, is described as

$$\mathrm{P}_{k,i}(y_{k,i} = s) = \frac{\exp(\tau_{k,s,c} - S_{k,i})}{1 + \exp(\tau_{k,s,c} - S_{k,i})} - \frac{\exp(\tau_{k,s-1,c} - S_{k,i})}{1 + \exp(\tau_{k,s-1,c} - S_{k,i})}, \tag{2}$$

where $(\tau_{k,s-1,c}, \tau_{k,s,c})$ is a range that $S_{k,i}$ needs to fall into for the respondent i to rate an s for contactless technology k, among all possible ratings from 1 to S; that is, the cutoff value of observable answers, $\tau_{k,s,c}$, describes the way respondents answer a rating scale question (the style). This style is specified as class-specific so that different groups of respondents exhibit different response styles. The response style groups are not observable but are determined by individual characteristics with an underlying logit structure

$$\pi_{i,c} = \frac{\exp(X_i \gamma_c)}{\sum_{c=1}^{C} \exp(X_i \gamma_c)}, \tag{3}$$

where $\pi_{i,c}$ is the probability that respondent i belongs to class c; X_i is the set of individual characteristics; and γs are the class-specific parameters that describe the influence of each individual characteristic on class allocation probability $\pi_{i,c}$.

Gender (GEN), age (AGE), city of residence (CTY), educational level (EDU), and income level (INC) are adopted to describe respondents' demographics, and travel frequency in 2019 (FRE), average budget per hotel stay (BGT), and usual travel companion (COM) are used to represent travel profiles. Given that the COVID-19 pandemic has had a severe impact on everyone's lives, especially from the travel and lodging perspective, respondents' concern regarding COVID-19 infection (COV) is included as a potential influential factor in accepting contactless technologies. Respondents' exposure to various types of contactless technologies (EXP), measured by the number of types of contactless technologies the respondents had prior experience with, is also considered influential in individual acceptance of contactless technologies.

The latent variables $DRIVER_i$ and $INHBTR_i$ are specified as functions of individual formative and situational experiences:

$$LV_{m,i} = f(GEN_i, AGE_i, CTY_i, EDU_i, INC_i, FRE_i, BGT_i, COM_i, COV_i, EXP_i) \quad (4)$$

with $LV_{m,i}$ being either a driver or inhibitor. These latent values ($LV_{m,i}$) are indicated by the corresponding item responses to the attitudinal questions:

$$I_{i,q} = \begin{cases} 1 & LV_{m,i} \leq \theta_{q,1} \\ 2 & \theta_{q,1} < LV_{m,i} \leq \theta_{q,2} \\ \vdots & \vdots \\ 7 & \theta_{q,6} < LV_{m,i} \end{cases}, \quad (5)$$

where $I_{i,q}$ are the observed ratings of attitudinal question q (TRI 2.0 items) and θs are cutoff parameters that link the respondents' latent attitude to their ratings. Figure 2 illustrates the path diagram of the model with rectangles representing observable variables; ovals representing latent variables; solid arrows indicating causal relationships; dotted arrows indicating indicative relationships; and shaded rectangles being model coefficients.

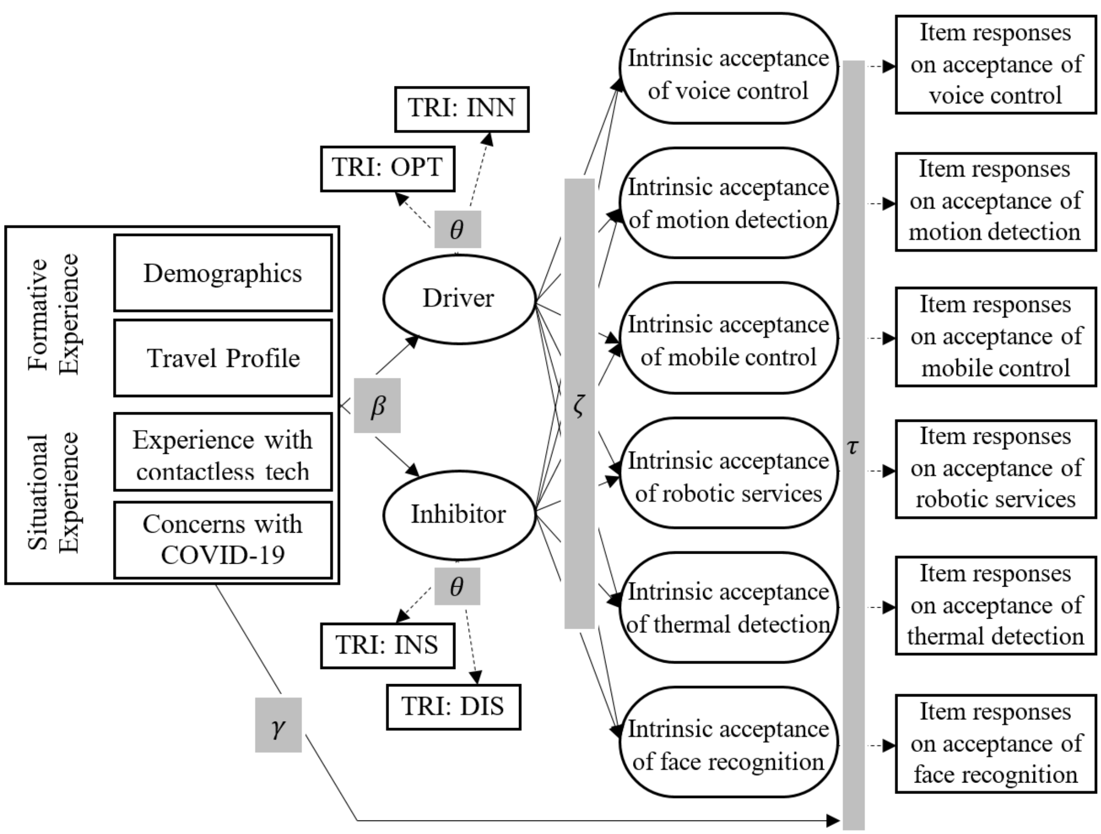

Figure 2. Path diagram of the proposed model

The models parameters described in Figure 2 can be estimated by a maximum simulated likelihood estimator with author-generated code based on the Apollo package in R (Hess & Palma, 2019a; 2019b). To find the optimal parameterization of the model, multiple variations of the model are tested and compared. More specifically, models with one, two, and four latent values (corresponding to model specifications using the TRI as a whole, two domains of the TRI, and four subdomains of the TRI, respectively), and models with two to four latent classes (response styles) are estimated.

Since the model is dealing with latent variables with arbitrary scale, some of the model parameters (such as β and ζ) are less meaningful in terms of their absolute value. Therefore, the estimates of β are standardized with the standard deviation of the respective latent value so that the interpretations of the coefficients are in the unit of standard deviation (SD) change in the latent value for each unit change in the influencing factor. The sign and relative magnitude of these coefficients reveal the direction and relative importance of each factor in the model components. The estimations of ζ describe the relationship between the two latent values—driver and inhibitor—and the individual intrinsic acceptance of contactless technology. Since the driver and inhibitor are unobservable with an arbitrary scale, only one of ζ_1 and ζ_2 can be identified in the model estimation for each contactless technology. In the present investigation, ζ_1 is normalized to unity, and the estimation of ζ_2 reflects the ratio of ζ_2/ζ_1, which describes the relative importance of inhibitor to driver.

4. Estimation Results

4.1 General model fit

Among different variations of model parameterization, the model specification with two latent values and three latent classes are found to outperform other parameterizations and are adopted in the subsequent analysis.

To evaluate the performance of the proposed model, three other benchmark models are estimated. The first model adopts a mixed feature in the ordinal logit model (MOL) to separately fit the acceptances of six contactless technologies. The MOL describes respondents' acceptance with stochastic heterogeneity without considering response style heterogeneity. The second benchmark model adopts a hybrid feature in the ordinal logit model (HOL) to separately fit the acceptance of the six technologies. The HOL advances the specification of the MOL with systematic heterogeneity, still without considering response style heterogeneity. The third benchmark model amends a theoretical drawback of the HOL, where technology readiness drivers and inhibitors are separately fitted across the estimations of acceptance of the six technologies. Conceptually, an individual's technology readiness is generic across types of contactless technology. Therefore, technology readiness drivers and inhibitors should be consistent for a specific individual across different estimations. The third model, denoted as the pooled hybrid ordinal logit model (POL), pooled the estimations of acceptance of the six technologies to improve consistency across estimates. The difference between the POL and the proposed latent class hybrid ordinal logit model with response style heterogeneity (hereafter LHOL) is the consideration of response style heterogeneity.

In general, the LHOL outperforms all the other models in terms of model fit and predictive power by achieving a log-likelihood on rating (LL) of -14288.7, a mean absolute deviation (MAD) of 0.7409, and a mean squared deviation (MSD) of 1.0547. Compared with the MOL (LL: -15788.5; MAD: 1.0330; MSD: 1.9819), the models with systematic heterogeneity (HOL, POL, and LHOL) achieved higher log-likelihoods, indicating the effectiveness of the additional model components in explaining individual acceptance of contactless technologies. In particular, the better model fit and predictive power of the HOL (LL: -15103.2; MAD: 0.8383; MSD: 1.3949) compared with the MOL indicate superiority in dealing with heterogeneity with a (systematic) hybrid model over a pure stochastic process.

Comparing the HOL and POL (LL: -15359.8; MAD: 0.8319; MSD: 1.3825) is more complex. The higher log-likelihood of the HOL reflects additional statistical flexibility by separately estimating six types of contactless technology acceptance, whereas the lower MAD and MSD of the POL indicate a superior explanatory power by pooling these six estimations together. This discrepancy between model fit and predictive power in comparing the HOL and MOL indicates a tradeoff between statistical flexibility and conceptual consistency. Since one of the objectives of the study is to understand the formation process of individual contactless technology acceptance, conceptual consistency should be given more weight in model selection. The specification that pools the estimations of acceptance of the six technologies (POL) is deemed better than the specifications with separate estimations (HOL).

The proposed LHOL significantly improves the general model fit and enhances the predictive power by achieving a 5.4% higher log-likelihood, 10.7% lower MAD, and 23.7% lower MSD than the best model specification among the other three. This result illustrates the effectiveness of incorporating systematic heterogeneity, enforcing conceptual consistency, and recognizing response style heterogeneity in understanding and modeling individual acceptance of contactless technology. In particular, the LHOL's superiority over the POL emphasizes the importance of modeling response style heterogeneity in analyzing Likert-scale data. Therefore, the remaining section focuses on the estimation of the LHOL to elaborate the role of individual experiences (formative and situational) in shaping an individual's acceptance of various contactless technologies and their response style in answering rating-type questions.

4.2 Intrinsic acceptance of contactless technology

Table 2 presents the standardized estimations of β, which describe the influence of individual sociodemographic information, travel profiles, COVID-19 concerns, and prior experience with contactless technology on the driver and inhibitor of accepting technology innovation. Male guests are more sensitive than female guests to technology innovations by exhibiting a 0.1289 SDs higher value in the driver domain and a 0.5227 SDs higher value in the inhibitor domain than the female respondents (H1a is supported). This result matches findings from other studies that males are more technologically concerned and curious in various contexts (e.g., Doss & Morris, 2001; Schumacher & Morahan-Martin, 2001).

The effect of age is similar to that of gender, in that older generations tend to place a higher value on both driver and inhibitor domains (H1b is supported). While the higher value in the inhibitor domain is consistent with the common idea that senior people are less technologically competent, the high value in the driver domain seems counterintuitive. Nonetheless, in an investigation on individual willingness to pay for services using contactless technology, Hao et al. (2022) suggested that senior people have a clear desire to embrace technological advancements.

Table 2. Relative importance of individual characteristics on latent values (β)

	Driver (LV_{DRIVER})	Inhibitor ($LV_{INHIBTR}$)
Gender (male)	0.1289*** [b]	0.5227**
(β_{GEN}/δ_{LV} [a])	(0.0290) [c]	(0.1106)
Age	0.2323****	0.3315****
(β_{AGE}/δ_{LV})	(0.0026)	(0.0346)
City of residence (1st tier)	0.0014	-0.4988****
(β_{CTY}/δ_{LV})	(0.0006)	(0.0501)
Education level (below undergrad)	-0.4264****	0.3113***
(β_{EDU}/δ_{LV})	(0.0599)	(0.0481)
Household income	0.5635****	-0.2524****
(β_{INC}/δ_{LV})	(0.0057)	(0.0291)
Frequency of hotel stay	0.3888****	-0.1984****
(β_{FRE}/δ_{LV})	(0.0232)	(0.0368)
Typical budget of hotel stay	-0.0834****	0.0051**
(β_{BGT}/δ_{LV})	(0.0115)	(0.0012)
Typical travel companion (kids)	0.4054****	-0.4083*
(β_{COM}/δ_{LV})	(0.0534)	(0.1105)
Concern of COVID-19 infection	-0.0279****	0.3449****
(β_{COV}/δ_{LV})	(0.0059)	(0.0256)
Previous experiences with contactless services (β_{EXP}/δ_{LV})	0.3016**** (0.0428)	0.0824** (0.0203)
Mean of LV [d]	3.3190	3.4023
Standard deviation of LV	0.6911	0.4974

[a] The unstandardized coefficients can be easily restored by multiplying the standardized coefficients with the respective standard deviation of the latent value at the bottom of the table.
[b] * significant at the 90% level; ** significant at the 95% level; *** significant at the 99% level; **** significant at the 99.9% level.
[c] Standard errors (SE) in parentheses.
[d] The individual level values are estimated with a 10,000 draws simulation using log-likelihood as the weights.

Respondents from first-tier cities do not differ significantly from those in other cities regarding the driver of technological readiness, but they are less hesitant in adopting technology innovations (H1c is partially supported). Frequent travelers, travelers with children, and individuals from households with a higher income are more confident and less hesitant in accepting new technologies than their respective counterparts (H1e,f,h are supported). However, acquiring an undergraduate education or higher seems to be a deterrent. These respondents have 0.4264 SD lower driver values and 0.3113 SD higher inhibitor values than those with lower levels of education (H1d is supported). This may be attributed to a higher level of information security awareness of more educated people (Öğütçü et al., 2016), since most technology advancements requires private information from individual.

Prior experience with contactless technology provides respondents with the necessary knowledge to embrace technological innovation (0.3016 SD increase in driver values), although these experiences also eliminate novelty and expose potential disadvantages, leading to a slight increase in inhibitor values (0.0824 SD) (H1j is supported). Respondents who typically stay in more expensive hotels have slightly lower driver and higher inhibitor values than those who choose budget hotels (H1g is supported). Hotel guests in luxury hotels might demand "warm" human services rather than "cold" machines, and the infrastructure and services provided in luxury hotels could satisfy this need.

Many studies have suggested that the COVID-19 pandemic would reshape perceptions of technology acceptance (e.g., Kim et al., 2021). However, the present study suggests a slightly different result. Respondents' COVID-19 concerns have a minor influence on the drivers of technology readiness and a positive relationship with technology readiness inhibitors (H1i is supported)—that is, respondents with greater concerns of COVID-19 infection are also more hesitant to adopt technology innovations. Those with high levels of concern about COVID-19 infection might be very risk averse, skeptical, and cautious. Therefore, it is reasonable for these respondents to exhibit strong doubts about technological innovations.

Table 3. Relative importance of latent values on intrinsic acceptances (ζ)

Type	Estimates	Type	Estimates
$\zeta_{2,voice}/\zeta_{1,voice}$	-0.4722** (0.2160)	$\zeta_{2,robot}/\zeta_{1,robot}$	-0.3901 (0.3280)
$\zeta_{2,motion}/\zeta_{1,motion}$	-0.2340**** (0.0396)	$\zeta_{2,thermal}/\zeta_{1,thermal}$	-0.5195**** (0.1472)
$\zeta_{2,mobile}/\zeta_{1,mobile}$	-0.7946*** (0.2719)	$\zeta_{2,face}/\zeta_{1,face}$	-0.2664** (0.1345)

Table 3 presents the relative importance of driver and inhibitor (ζ_2/ζ_1). All the estimates are negative and statistically significant, except for the ratio for robotic contactless technology (H2 is partially supported). The negative sign indicates opposite influences of driver and inhibitor in determining individual acceptance of contactless technology, whereas the magnitude of the ratio reflects the relative importance of driver and inhibitor in forming the acceptance level of each contactless technology. In general, the inhibitor is less important than the driver while respondents are considering accepting a contactless technology. For instance, the inhibitor is about 80% as important as the driver for mobile control. The importance of the inhibitor is reduced to approximately half of the importance of the driver for voice control and thermal detection, and to approximately a quarter of the importance of the driver for motion detection and face recognition. Regarding robotic services, the influence of the inhibitor is statistically insignificant on average.

The estimations of β describe how individual characteristics influence driver and inhibitor values, whereas the estimations of ζ reflect the link between technology readiness driver/inhibitor and intrinsic acceptance of contactless technology. The operation $(\beta_{DRIVER} + \beta_{INHBTR} \cdot \zeta_2/\zeta_1)$ gives the net effect of individual characteristics on intrinsic acceptance of contactless technology. Table 4 presents these results.

Table 4. Net effect of characteristics on intrinsic acceptance

	Voice control	Motion detection	Mobile control	Robotic services	Thermal detection	Face recognition
Gender (male)	-0.0337	0.0283	-0.1175	-0.0123	-0.0460	0.0198
Age	0.0827	0.1220	0.0295	0.0962	0.0749	0.1166
City of residence (1st tier)	0.1181	0.0590	0.1981	0.0977	0.1298	0.0670
Education (below ugrad)	-0.3678	-0.3309	-0.4177	-0.3551	-0.3751	-0.3359
Household income	0.4487	0.4188	0.4891	0.4384	0.4546	0.4228
Travel frequency	0.3370	0.3025	0.3837	0.3251	0.3439	0.3072
Hotel budget	-0.0588	-0.0582	-0.0597	-0.0586	-0.0590	-0.0583
Travel companion	0.3761	0.3277	0.4415	0.3594	0.3857	0.3343
COVID concern	-0.1003	-0.0594	-0.1556	-0.0862	-0.1084	-0.0650
Previous experiences	0.1891	0.1988	0.1759	0.1924	0.1871	0.1975

Among the six contactless technologies, male respondents have higher intrinsic acceptance of motion detection and face recognition, whereas female respondents are more inclined toward voice control, mobile control, robotic services, and thermal detection. Older generations, first-tier city residents, respondents with a higher household income, frequent travelers, those traveling with kids, and respondents with rich prior experience with contactless technology embrace all types of contactless technologies. In contrast, respondents with higher education levels, those who choose luxury hotels, and those with greater COVID-19 concerns are conservative in accepting contactless technologies.

In terms of relative magnitude, being a first-tier city resident has the least marginal effect on intrinsic acceptance of contactless technology, whereas traveling with kids, being a frequent traveler, and not acquiring an undergraduate degree have marginal effects of 3 to 3.5 times larger. The marginal effects of the other factors are not entirely comparable due to differences in units. However, caution is needed when considering the marginal effects on robotic service because the estimation of ζ_2/ζ_1 associated with robotic services is not statistically significant.

A numerical simulation of all respondents' intrinsic acceptance uses their individual characteristics and the estimation results. The simulation follows the procedure introduced in the "conditional" function in the Apollo package (Hess & Palma, 2019a; 2019b), with 10,000 random draws on the random component and conditional log-likelihood as weightings. The simulation results reflect the estimated individual intrinsic acceptance of all contactless technologies. In general, the contactless technologies that people experienced extensively during the pandemic—mobile control and thermal detection—have the highest values (mobile control = 3.57; thermal detection = 3.43), whereas the technology with the most privacy concerns—face recognition—has the lowest value (2.36). The higher standard deviations for mobile control (SD = 1.4191) and thermal detection (SD = 1.0246) indicate more variation in opinions on these two technologies. Although they are more accepted by the public than the others, this acceptance is not universal. The skewness (SK) of all acceptance values is positive, indicating more density at the lower end of each distribution—that is, more respondents have below-average acceptance values. The case is more severe for mobile control (SK = 1.1878) and thermal detection (SK = 1.1687), the two technologies with higher overall acceptance. It is noteworthy that the low intrinsic acceptance value is relative to the sample mean and does not indicate low acceptance ratings in the survey questions.

4.3 Heterogeneity in response styles

In addition to the systematic acceptance heterogeneity captured by the hybrid choice feature, the LHOL specifies heterogeneity in response styles. A model with three latent classes is chosen after comparing models with two to four latent classes. According to the estimation, the three classes have 52 (2.70%), 292 (15.15%), and 1583 (82.15%) members within the sample. The class-specific τ reflects the response styles in each class, which is further illustrated with a spectrum (Figure 3). The vertical axis in Figure 3 reflects the individual level of intrinsic acceptance of contactless technology. The observed ratings of 1 through 7 correspond to red, orange, yellow, green, cyan, blue, and violet, respectively. Warmer colors indicate less acceptance and cooler colors indicate more acceptance. The faded ranges are intervals beyond 3 SDs from the mean of intrinsic acceptance values and deserve less attention. The three spectra for each contactless technology type present the acceptance of classes 1 to 3 from the left to the right.

Class 1 respondents are less likely to choose 5, 6, or 7 for all the contactless technologies and are described as *critics*, as they are more reluctant to choose "strongly accept." Compared with other guests, *critics* tend to rate voice control and face recognition lower (1, 2, or 3) than motion detection, mobile control, robotic services, and thermal detection. *Critics* are the most conservative guests in the market, and the proportion of *critics* in the market is low.

Respondents from two other groups, *complimenters* (class 2) and *mainstreamers* (class 3), are more likely than *critics* to give high ratings about accepting contactless technology. These two classes of respondents have similar spectra, with *complimenters* having a slightly tighter range for all contactless technologies, except for voice control—that is, *complimenters* are more likely than others to give high ratings. *Mainstreamers* have a moderate response style and represent a large proportion of the market. Regarding accepting voice control, *complimenters* give higher ratings overall than *mainstreamers*.

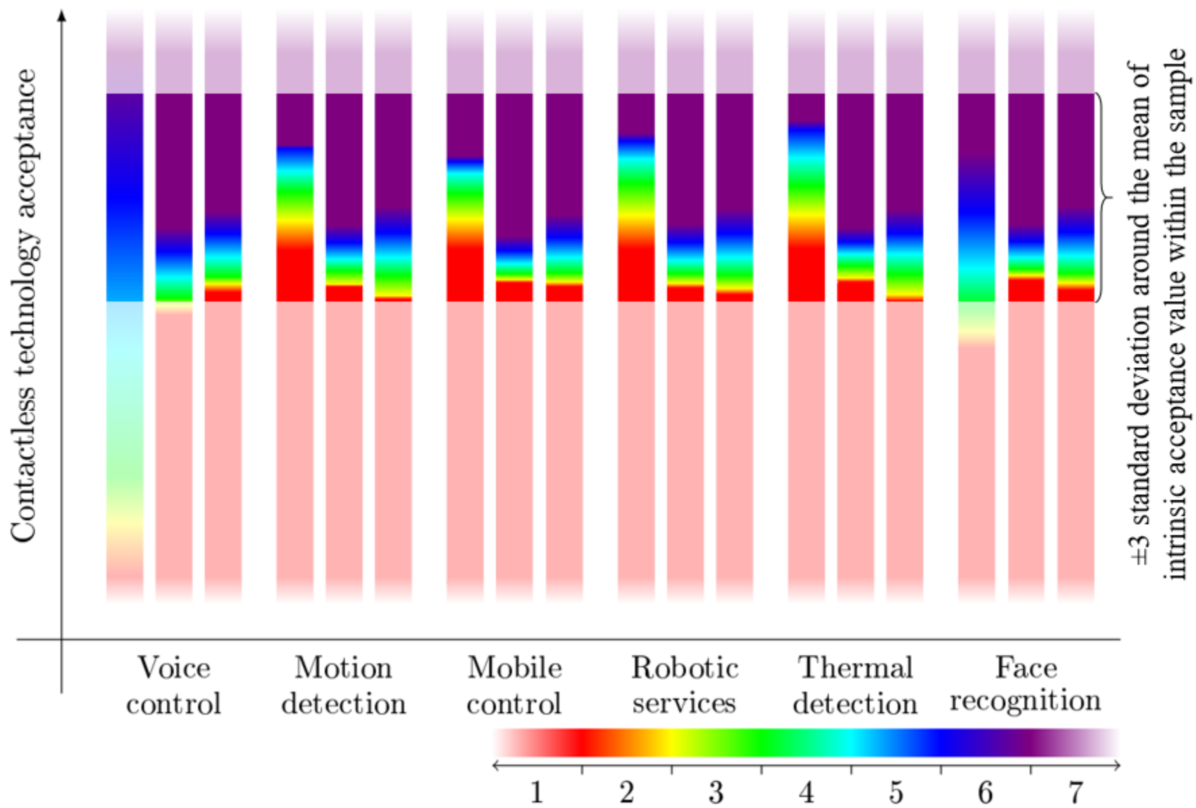

Figure 3. Heterogeneities in response styles (τ)

The estimates of γ control the class allocation of each respondent (Table 5; H3a,b,c,d,e,f,g,i,j are fully supported and H3h is partially supported). As indicated earlier in the model fit and predictive power comparison, the LHOL, which incorporates response style heterogeneity, outperforms the POL without considering response style in the model (H4 is supported). Due to the logit structure of class allocation probability (Equation 3), the absolute magnitude of each coefficient is uninformative. Nevertheless, the signs and relative magnitudes of the coefficients describe the direction and importance of each individual characteristic on class allocation, respectively. Positive and larger coefficients on a characteristic indicate an increase in the odds of a respondent belonging to a specific class. It should be emphasized that response style class does not influence individual intrinsic acceptance of the various contactless technologies but merely determines how intrinsic acceptance is reflected in the ratings. Heterogeneity in intrinsic acceptance is controlled by individual characteristics and the net effects of these characteristics (Table 4).

Table 5. Relative importance of individual characteristics on class allocation (γ)

	Critics	*Complimenters*	*Mainstreamers*
Gender (male)	51.10***	-24.37****	-23.73****
(γ_{GEN})	(19.581)	(3.4571)	(3.3160)
Age	-8.32****	5.08****	6.23****
(γ_{AGE})	(1.9059)	(0.7071)	(0.7577)
City of residence (1st tier)	34.33****	-15.79****	-15.55****
(γ_{CTY})	(7.8758)	(4.4385)	(4.4582)
Education level (below undergrad)	-24.27**	13.20****	14.08****
(γ_{EDU})	(9.8775)	(2.2065)	(2.4613)
Household income	-7.86***	4.72**	6.14***
(γ_{INC})	(2.7536)	(1.9915)	(1.9847)
Frequency of hotel stay	-10.09***	6.81****	6.28***
(γ_{FRE})	(3.4493)	(1.9493)	(2.0347)
Typical budget of hotel stay	-43.37****	22.81***	23.56***
(γ_{BGT})	(11.796)	(7.0943)	(7.2351)
Typical travel companion (kids)	2.68**	1.14****	-0.23
(γ_{COM})	(1.2692)	(0.2151)	(0.1432)
Concern of COVID-19 infection	12.36****	-4.85****	-4.51****
(γ_{COV})	(2.0885)	(1.1569)	(1.0790)
Previous experiences with contactless services (γ_{EXP})	8.74**** (2.1376)	-1.91*** (0.6776)	-3.83**** (0.6490)

Critics are more likely to be men with children who live in first-tier cities, have abundant experience with contactless technology, and be concerned about the pandemic. Although respondents who live in first-tier cities, travel with kids, and have prior experience with contactless technology are more likely than their counterparts to have high intrinsic acceptance of contactless technologies (according to the net effects in Table 4), they do not rate as high on the acceptance rating scale as other respondents with similar levels of intrinsic acceptance.

Compared with *critics*, *complimenters* and *mainstreamers* tend to be older and better educated, have higher household incomes, travel more frequently, and stay in hotels that are more expensive. These two classes are similar in terms of individual characteristics, except for typical travel companions. *Complimenters* travel more with children than *mainstreamers* do. Slight differences are also identified between these two classes regarding age, household income, and prior experience with contactless technologies. *Mainstreamers* are older and richer but less experienced with contactless technology.

5. Discussions and Conclusions

This study focused on heterogeneity in hotel guests' acceptance of contactless technology by examining this heterogeneity from two sources: intrinsic technology acceptance and response styles. Matching results from other technology readiness research, our findings show that hotel guests exhibit different levels of technology readiness, which lead to varied levels of intrinsic acceptance of contactless technologies. Heterogeneity in individual technology readiness originates from formative and situational experiences (e.g., demographics, travel experiences, contactless technology engagement, and pandemic concerns). This study also indicates that hotel guests have heterogeneous response styles in answering rating-scale questions. Individuals with the same level of intrinsic acceptance of contactless technology may respond differently according to their response styles, resulting in observed variations in expressed opinions. This study confirms the existence of both heterogeneity sources and provides a more accurate description of hotel guests' acceptance of contactless technology. These findings contribute to the literature regarding five main aspects.

First, the study's model incorporates response style heterogeneity in the analysis of rating scales that measure latent continuous variables. The LHOL model's superiority not only demonstrates the need to consider response style in such analyses but also proposes a viable way to handle response style heterogeneity through latent class ordinal logit models. Future research using rating scales should take response style biases into consideration to capture heterogeneity from different channels and generate more accurate estimates.

Second, this study identifies two distinct sources of heterogeneity, making a theoretical contribution to the literature on hotel guests' technology acceptance and choice. By incorporating response styles into our model, we provide a more accurate estimation of hotel guests' contactless technology acceptance and respond to concerns about distorted market analysis results from data quality issues in rating scales (Grün & Dolnicar, 2016). Theoretically, the two sources of heterogeneity have distinct impacts on people's behavior. Intrinsic acceptance directly influences hotel guests' adoption of contactless technologies, whereas response style influences how hotel guests express themselves. Without direct influence on contactless technology adoption, the way hotel guests express themselves regarding contactless technology may alter the information disseminated through social interactions and influences the acceptance of contactless technology in the market in general.

Third, our model incorporates the “hybrid” idea from the hybrid choice model into the ordinal logit model to enhance the identification of latent values. Our results extend the research on two indicators (drivers and inhibitors) of technology readiness, which bridge individual characteristics and intrinsic acceptance of contactless technology. Existing studies applying the TRI have highlighted the significance of positive readiness (drivers including optimism and innovativeness) in forming individuals’ beliefs or decisions (Shin & Jeong, 2022; Wang et al., 2017), and the driver domain is more important than inhibitors when hotel guests decide to embrace contactless technology. Our research findings confirm the important role of driver domain and further discovered heterogeneity in this relative importance of driver and inhibitor domains in accepting multiple types of contactless technologies. More specifically, individuals’ technology readiness drivers take on greater importance for specific technology types, such as motion detection and face recognition, whereas the importance of inhibitors is 80% similar to the driver for mobile control. In short, accepting contactless technology in hotels is not universal but depends on technology types, as well as individuals’ characteristics and inclinations toward technological innovation.

Fourth, in response to the arguments about the impacts of COVID-19 on the post-pandemic hotel guests’ technology acceptance, which may be salient (Kim et al., 2021) or marginal (Hao et al., 2022), this study provides additional empirical evidence about guests’ mindsets toward contactless technology. Unlike existing discussions about the COVID-19 pandemic being a facilitator of disruptive technologies, our findings reflect that Chinese hotel guests regard contactless technology not as a remedy for the COVID-19 crisis but as a general trend in an accelerating world. This may be attributed to the timing of the data collection as also argued in Hao et al. (2022): around December of 2020, the average daily new cases of COVID-19 infection were below 30 in China and the respondents expressed limited concern about the pandemic. This finding implies that the facilitating effect of the COVID-19 pandemic on disruptive technologies may not be long-lasting. Therefore, the lesson for tourism firms or hotels that have got through the recent global pandemic is that the opportunity window is rather narrow if they want to take a health crisis to promote their contactless technology adoption. But rather, positioning contactless technology as hotel technology amenities in the new normal service environment would be more effective to enhance customers' acceptance. Aligning with current arguments, such as those by Liu et al. (2022), it is important to understand the dynamics that shape customers' reactions to technology-enabled services in response to the pandemic.

Fifth, our findings regarding two distinct heterogeneous sources of technology acceptance generate important managerial implications for marketing in hotel and tourism organizations. The results on the link between individual characteristics and intrinsic acceptance could help with precision marketing plans. When practitioners introduce contactless technology to the market, they could examine customers' tendencies toward innovations to analyze who is less hesitant to adopt them. This practice could help define primary markets with higher acceptance groups and establish marketing plans for reducing consumer resistance to contactless technology-based services. One caution, however, is that tourism suppliers providing luxury experiences, such as luxury hotels and cruises, should pay greater attention to balancing high-touch and high-tech experiences.

The findings on heterogeneous response styles highlight another important issue for marketing teams. Response styles reflect how people express themselves and have significant impact on WOM behaviors (Singh, 1990). Understanding response styles is essential for hotels and tourism firms when using WOM as a marketing tool. A person who always give high ratings (e.g., *complimenters*) is also likely to say good things about a product or technology when talking to others. Enhancing *complimenters*' acceptance of a product could improve the effectiveness of WOM through social interactions. In contrast, *critics* are less likely to express strong acceptance in conversations with others. Firms should try to mitigate reluctance among *critics* to prevent discouraging WOM in their networks. Despite its relatively small class-size found in our research (2.7% of the sample), *critics* are the main source of complaints that lead to negative social interaction effects. Practitioners should avoid service failures in this group and target high acceptance groups when introducing technology innovations.

Two main study limitations should be acknowledged. First, the survey was conducted only in China, one tourism source market that is perceived to have the most tech-savvy group of tourists (Wu et al., 2020). As culture can influence technology readiness and response styles and prior experiences with technology has a positive influence on people's acceptance of new technologies, the magnitude of influences and acceptances discovered in this study may be higher than those of other cultures and regions. Future studies should examine the generalizability of our model across cultures and investigate whether hotel guests from other regions show two sources of heterogeneity in contactless technology acceptance. Second, the timing might have influenced the responses. The data were collected near the end of 2020, when Chinese customers had been experiencing the COVID-19 pandemic for a year and the industry and society were gradually recovering from the crisis. Whether due to confidence in coping with COVID-19 or "pandemic fatigue," changing influences may have occurred in COVID-19 concerns and their impact on technology acceptance. Examining guests' acceptance of technology-enabled services in the post-pandemic era or in a more general health crisis scenario would be worthy of additional investigation.

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