Proceedings of the 54th Hawaii International Conference on System Sciences | 2021

How Do Customers Respond to Robotic Service? A Scenario-Based Study from the Perspective of Uncertainty Reduction Theory

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Abstract

Confronted with an increasing popularization and advancement of applying artificial intelligence in robotic technology, practitioners in the service sector have been increasingly deploying service robots in their operations. Motivated by a paucity of knowledge on how consumers would respond to the robotic service, this study establishes on the uncertainty reduction theory to advance a research model that seeks to unveil how both customer trait and service characteristic affect customers' revisit intention to robotic service via perceived risk. Based on a scenario-based experiment with 190 responses in the hotel reception service context, our results reveal that perceived risk partially mediates the relationship between personal innovativeness and service revisit intention, so does between service heterogeneity and revisit intention. Furthermore, the service context, i.e., whether the prior service experience satisfies the customer, can moderate the relationship between personal innovativeness (service heterogeneity) and perceived risk. This study also draws related theoretical and practical implications.

1. Introduction

The incorporation of artificial intelligence (AI) into the service sector finds expression in service robots' deployment. The proliferation and advancement of robotics have boosted the drive to replace humans with robots in the service sector, especially in tourism and hospitality [1], [2]. Concretely, there is an increasing trend that service robots come forward to the realms of hospitality operations, such as the services reception, delivery, and in-room companion [1], [3]. Under this circumstance, it is essential to figure out how customers respond to service robots' deployment and what outcome will result. However, there is a paucity of literature addressing this research question.

This study seeks to understand customers' response to robotic service from the lens of uncertainty reduction theory (URT). URT offers accounts for information-seeking strategies facing uncertainty [4], which allows explicating the role of both customer trait (personal innovativeness) and service characteristic (service heterogeneity) in robotic service adoption. In the context of URT, the subject (either an individual or an organization), while experiencing uncertainty, is motivated or driven to seek information to reduce uncertainty.

Personal innovativeness is conceptualized as an individual trait that reflects one's willingness to try new technology [5] and individual tolerance of risk [6]. Thus, personal innovativeness can be seen as a channel of uncertainty reduction, with considerable attention having been paid to the influence of personal innovativeness on innovation adoption [7], [8]. The service robot is a comparatively novel concept compared with human counterparts in the hospitality industry, bringing more uncertainty. In this line, increased personal innovativeness, which translated into promoted individual competence to cope with innovations, can be argued as a strategy for mitigating uncertainty and perceived risk. Therefore, it is worthwhile to examine the impact of personal innovativeness on robotic service adoption.

Heterogeneity is one of the four fundamental characteristics that distinguish services from tangible products, together with intangibility, simultaneity, and perishability [9]. Service heterogeneity refers to an attributive characteristic of service that arises from variability concerning service providers, customers, service times, or service sites [10]. Heterogeneity suggests that all service performance is somewhat different [11], and customers can expect future delivered service depending on the degree of perceived service heterogeneity [12]. In this vein, service heterogeneity can be viewed as an external cue that affects customers' uncertainty and behavioral outcomes. While previous studies allude to the importance of service heterogeneity in understanding customers'

URI: https://hdl.handle.net/10125/70681
978-0-9981331-4-0

perceptions and service experience [10], [13], little is known about its effects in the context of robotic service. This study investigates customers' responding process to the service delivered by robots by explaining the role of personal innovativeness and service heterogeneity based on URT.

Apart from customer and service characteristics, whether the previous service experience is satisfied can also influence customers' perceptions [14]. This study argues that customers' perception of service robots is contingent on prior service experience (satisfied or dissatisfied). Therefore, this study explores how customers' perceptions derived from customer and service characteristics differ under the respective conditions of having a satisfying or dissatisfying prior service experience.

2. Theoretical Foundation

2.1 Personal innovativeness

In consumer psychological literature, personal innovativeness refers to a generalized individual personality trait that links to one's competence to accept innovations [15]. Following Roger [16], personal innovativeness is defined as an individual predisposed tendency toward adopting innovation, and individuals behave variously toward any new service or goods on account of their variability in innovative character.

Notably, previous studies have identified personal innovativeness as one of the significant determinants of the adoption and diffusion of innovative technologies [16], [17]. Several scholars have found evidence that personal innovativeness significantly contributes to the adoption of either new products or services [18], [19]. For instance, Im et al. [20] view personal innovativeness as a kind of higher-order personality trait, which exerts both direct and indirect effects on new product adoption. Further, personal innovativeness has also been identified as a critical construct in online shopping adoption and significantly associated with increased online shopping intention [21]. Yet, little is known when applying personal innovativeness in the context of robotic service or the effect of personal innovativeness on robotic service adoption.

2.2 Service heterogeneity

Service heterogeneity, also dubbed service variability, concerns "the potential for high variability in the performance of services" [22, p. 124]. Service heterogeneity arises when different individuals are involved in service delivery [10], which is more so for more labor-intensive service [23]. Past studies imply that service delivery's heterogeneity mainly derives from the variability of the service providers [23], [24], because different service providers have different personalities, service delivery skills, and attitudes to customers, to name but a few [24]. Moreover, even the same service provider might deliver differentiated service performance.

According to a systematic literature review of 46 academic articles, heterogeneity in service acts as a significant conceptual notion for understanding customer perception and service adoption. Heterogeneity can induce a feeling of uncertainty [25], which is one of the main antecedents of perceived risk [26]. In this vein, a higher level of service heterogeneity may increase customers' perceived risk of the received service, which in turn can deteriorate purchase intention for services [27]. Several studies offer empirical support for this assertion. For example, Roy & Sivakumar [10] convey that heterogeneity in service enables one to have negative implications for customer experience, which might further contribute to negative perceptions. The work of Agudo-Peregrina et al. [28] demonstrates that, in the context of online service, customers prefer homogeneous service to heterogeneous service because customers receiving homogeneous service have lower perceived risk and thus higher intention to purchase the service.

Although the conceptualization of heterogeneity has been well documented in service science, few studies have discussed service heterogeneity and its effects in the novel context of robotic service. Accordingly, this study aims to explore customers' response to robotic service through the lens of service heterogeneity in service encounters.

2.3 Uncertainty reduction theory

Uncertainty reduction theory (URT) suggests that, during the initial interactions, the primary concern of individuals is to reduce uncertainty about the interaction behavior between the individuals and their partners [4][29]. To minimize uncertainty and maximize predictivity, there are three general categories of information-seeking strategies in URT, including passive, active, and interactive strategies [30]. The passive strategy for an individual is to obtain information involving the target partners via unobtrusively observing their behaviors. In contrast, the active strategy is to proactively obtain information about the target partners from third parties or the environment. The interactive strategy, however, involves directly seeking information through confronting the target partners, such as direct interaction or interrogation. In summary, uncertainty reduction is primarily bent on seeking or gathering relevant information to increase predictability and decrease the perceived risk of outcomes.

Despite uncertainty reduction originating from the interpersonal communication field, URT has also been adopted as an underlying theory in consumer behavior. For instance, Shin et al. [31] find that both interactive and passive uncertainty strategies positively and significantly contribute to continuous visiting social networking behavior through the mediator of a low level of uncertainty. Venkatesh et al. [32] verify that both information quality and channel characteristics predict citizens' intentions to use e-government via drawing from URT. Similarly, in the setting of online shopping, Racherla et al. [33] provide evidence that product reviews with either argument quality or perceived similarity contribute to increased customers' trust.

However, intangible services are perceived to be riskier than tangible products [34], considering the four above mentioned characteristics differentiating services from products [9]. As a result, customers tend to seek relevant information to reduce the uncertainty concerning services [34]. They utilize both external (such as environmental information [32]) and internal (such as prior service experience [35]) sources to acquire information and reduce the uncertainty of delivered service. Accordingly, in the context of robotic service, this study contends that the origin of perceived risk (dominantly arising from uncertainty) is anchored in both parties of service robots and customers. Therefore, customers' perception of the coming service encounter relies highly on individual competence, robotic service characteristics, and prior service experience. Nevertheless, few studies have employed the uncertainty reduction theory to explore how customers respond to robotic service. Guided by URT, this study examines the relationship between personal innovativeness (as well as service heterogeneity) and service revisit intention through the mediating effect of perceived risk.

3. Hypotheses Development

Individuals with higher innovativeness are more likely to adopt innovations earlier than others [36]. Although numerous factors, such as knowledge and exposure to technologies, contribute to the development of personal innovativeness, individuals' willingness to adopt uncertainty and their risk-taking ability are most significant for being innovators and early adopters [36]. Past studies have identified the positive role of personal innovativeness in technology adoption and risk perception reduction in various contexts of, for example, telephone shopping [37], online banking services [19], [38], and online shopping [21].

As a novel expression of AI technology, robotic service brings customers an innovative form of service delivery, which may trigger a feeling of uncertainty [39]; uncertainty is one of the significant precursors of risk perception cultivation [26], [40]. Following URT, it is conceivable that people with a higher competence to cope with uncertainties tend to have lower risk perception. Even in situations where service robots failed to perform successful services, customers with greater innovativeness can be more competent to deal with service failure and perceive lower risk. Thus, we hypothesize that:

H1: Personal innovativeness negatively associates with perceived risk.

Service failure is inevitable during service delivery, especially in tourism and hospitality [41]. Given the possibility of mechanical malfunctions and customer misoperations, service failure is also likely to occur in robotic service. In particular, since service robots' deployment is at the very initial stage nowadays, robots are still directional to delivering inconsistent service.

Past studies suggest that service heterogeneity enables customers to predict the service they are likely to receive [12]. The higher heterogeneity in the provision of service, the more difficult it will be for customers to predict the service quality they are going to receive, since higher service heterogeneity conveys more variability and uncertainties in the service *per se* [25]. Considering the positive association between uncertainty and perceived risk [26], [40], more heterogeneous service can trigger more uncertainties about the service that customers are likely to experience, leading to higher risk perception. Thus, we hypothesize that:

H2: Service heterogeneity positively associates with perceived risk.

The sources of risk perception include such two dimensions as uncertainty and adverse consequences of the receiving innovations [40]. Customers' risk perception acts as a primary obstacle to adopt innovations, including products, services, and ideas [19]. Findings across different research contexts suggest the negative effect of perceived risk on adoption intention. For instance, as demonstrated in the case of tangible goods, past studies have found that perceived risk significantly decreases customers' willingness to purchase online [21]. A similar conclusion about the negative effect of perceived risk on consumers' service adoption has also been drawn in online banking services [19], [38] and tourism [42]. In this line, if customers have a higher risk perception for the service delivery, they are less willing to adopt the robotic service, reflecting on reduced intention to re-patronize the service. Thus, we hypothesize that:

***H3*: Perceived risk negatively associates with service revisit intention.

The previous service performance acts as a significant basis to predict future service performance [43]. Either successful or unsuccessful service may happen in the robotic service. When the service robot has already delivered favorable service, there is a high possibility that it will consistently satisfy the customer in the future service because robots behave under pre-designed patterns. In such a situation, customers' risk perception may be reduced, and the alleviating effect of personal innovativeness on perceived risk can be strengthened. Contrarily, when a service failure occurs, given the relative inflexibility and consistency of robotic service, the customer would expect to receive consistently unfavorable service next time, thereby perceiving higher risk. This may weaken customers' confidence in experiencing satisfying service next time even if they have high risk-taking competence. Thus, we posit:

***H4*:** Service context moderates the relationship between personal innovativeness and perceived risk.

In view of the inevitability of service failure during service delivery [41] and the significance of service heterogeneity in service prediction [12], we assume that the relationship between service heterogeneity and perceived risk is contingent on the prior robotic service performance. When customers received satisfying service, higher service heterogeneity conveys more uncertainties and a higher likelihood to receive future service differing from the previously satisfying one, thereby strengthening their risk perception. On the flip side, it is reasonable for the dissatisfied customer to infer that greater service heterogeneity makes the next delivery service greatly different from the prior unsatisfactory service, that is, more likely to be favorable. This inference, therefore, reduces customers' perceived risk. Thus, we posit:

***H5*:** Service context moderates the relationship between service heterogeneity and perceived risk.

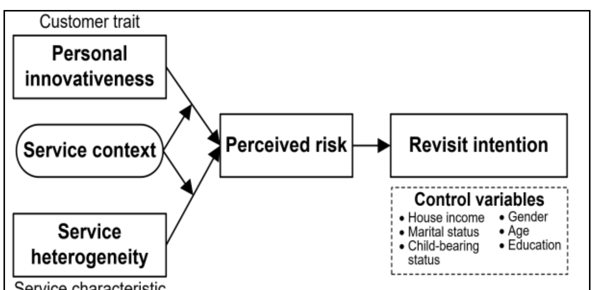

Figure 1. Research Model

Following previous studies [12], [44], this study covers several control variables in the research model to ensure the robustness of data analysis (see Figure 1).

4. Methodology

This study employs a scenario-based experiment to verify the proposed research model. The scenario-based design has been extensively used in the information system (IS) research [45]. The scenario is conceptualized as a situation description that assumes to happen in the potential future, having been widely employed in experimental studies that need to manipulate various conditions of variables, simulate response tasks, or represent a research context [46]. With a scenario-based experiment, a participant is first required to carefully go through one or more scenarios that contain a subset of the experimental treatments; and then respond to a survey based on their perceptions of each scenario.

4.1 Study design

4.1.1 Scenario setting. Given the increasing deployment of service robots in hospitality and representativeness of robot bellhops in reception service [3], this study singles out hotel robot receptionists as research objects. To create qualified scenarios, we first studied all the available Tripadvisor reviews of *Henn-na* Hotel in Japan (*N* = 162, Retrieved January 8, 2020), which is the first hotel using service robots in its entire service operational process from 2015. Using both positive and negative reviews related to the robot receptionist, we set up two scenarios reflecting the actual successful and unsuccessful performance of robot receptionists.

Since "*context defines the conditions experienced by the users*" [47, p. 352], the service condition experienced by the customer is termed as "service context". The satisfying service context (Scenario I) and dissatisfying service context (Scenario II) refer to where customers use robot receptionists successfully and unsuccessfully, respectively. For the robustness of the created scenarios, an expert review panel consisting of four IS researchers was convened for assessing each scenario's realism and validity [48]. Based on the panel's feedback, improvement for the scenarios' description was made to enhance its reliability and reduce overall ambiguity [49]. The final scenario descriptions can be found in *Supplementary Materials*.

4.1.2 Measurement. Considering that few suitable measurements of service heterogeneity are available, we self-created eight measurement items for service heterogeneity following the recommended procedure in previous studies [50], [51] (See *Supplementary Materials*). Measurement scales for the other three constructs, i.e., personal innovativeness [17], [52], perceived risk [53], [54], and revisit intention [55] were adopted from the previous literature. To guarantee adequate reliability and validity of these constructs, we conducted a pre-test with 60 respondents and improved the survey based on their feedback.

4.2 Data collection

All the respondents are from Amazon Mechanical Turk (MTurk). Those who completed the experiment would receive one USD as compensation. As Figure 2 illustrates, once completing a consent statement, participants would be asked about their experiences with hotel services. Those without any hotel accommodation experience in the past 12 months were excluded from this study. Then, participants needed to watch a one-minute video about how a robot receptionist works at the front desk (See *Supplementary Materials*), following which they were required to answer two questions about the video content to ensure they earnestly watched the video. Those who failed to offer correct answers would be excluded. Subsequently, the remaining participants were randomly assigned to one of the two created scenario descriptions. After reading the scenario description, they were asked to respond to two attention-check questions about the scenario description to guarantee they correctly understood the distributed scenario. Those who failed to pass the attention-check were excluded from the study. Note that participants who did not pass the attention-check embedded in the survey questions were also dropped.

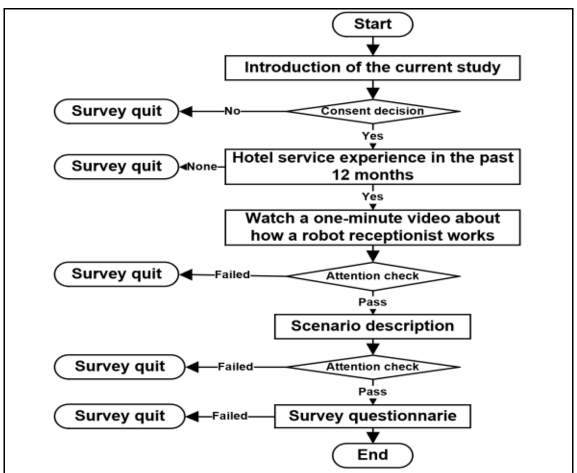

Figure 2. Experimental Procedure

This study screened the collected responses and discarded unmindful responses that provided almost the same answer for each question, and those with a responding time less than 150 seconds. Finally, 95 responses for each scenario were obtained, amounting to a final sample size of 190. Table 1 presents the respondents' demography.

Table 1. Demography of Participants

Variables	Categories	Count	
		S I	S II
Gender	Male	64	57
	Female	31	38
Age	18-25 years old	3	6
	26-35 years old	47	41
	36-45 years old	23	33
	46-55 years old	17	7
	56-65 years old	5	6
	66 years old & above	0	2
Education	Less than high school	1	0
	High school	20	17
	Bachelor's degree	59	58
	Master's degree	11	17
	Ph.D.	4	1
	Trade school	0	2
Marital status	Yes	50	41
	No	45	54
Child-bearing status	Yes	55	58
	No	40	37
House income	Less than $25,000	10	10
	$25,000-50,000	31	37
	$50,000-$100,000	38	35
	$100,000-$200,000	15	11
	More than $200,000	1	2

Note: SI means Scenario I; SII means Scenario II.

5. Data Analysis

This study utilizes the structural equation modeling (SEM) technique via SmartPLS 3.3 to test the proposed hypotheses. The SEM technique enables us to analyze both measurement and structural models [56]. Following the recommended procedure [57], the measurement model was first tested. After ensuring that all the constructs achieved adequate parameters for the path test, the structural model was tested.

5.1 Test of the measurement model

To verify the measurement model, we estimated the internal consistency and (convergent and discriminant) validity of the measurement items covered in our survey instrument. Since the reflective item captures the influence of the construct under scrutiny [58], we can assess internal consistency via three indictors: Cronbach's alpha, composite reliability

(CR), and average variance extracted (AVE) [59]. Table 2 suggests an adequate level of internal consistency [60]. Further, convergent and discriminant validity of the measurement items were evaluated. All the factor loadings of the latent constructs exceed prescribed thresholds of 0.7, showing good convergent validity [59]. For discriminant validity, the AVE's square root for each construct was compared against its correlations with other constructs [59]. To gain sufficient discriminant validity, the AVE's square root for every construct should be higher than any relevant bivariable correlations. The correlation matrix in Table 3 displays adequate discriminant validity. Since each bivariable correlation among the five latent constructs in our measurement model is much lower than corresponding AVE's square root, respondents can differentiate among the constructs in the theoretical model while filling in the questionnaire. In addition, individual items loadings beyond 0.5 on their associated factors further confirm both convergent and discriminant validity.

Table 2. Internal Consistency and Validity

	Minimal factor-loading	Cronbach's Alpha	CR	AVE
PR	0.942	0.964	0.974	0.904
PI	0.804	0.922	0.941	0.801
RI	0.957	0.975	0.981	0.930
SH	0.809	0.951	0.958	0.743

Notes: PR = Perceived risk; PI = Personal innovativeness; RI = Revisit intention; SH= Service heterogeneity. Criteria:Cronbach's alpha > 0.70; CR > 0.70; AVE > 0.50 [60].

Table 3. Correlations

	PR	PI	RI	SC	SH
PR	**0.951**				
PI	-0.203	**0.895**			
RI	-0.652	0.325	**0.964**		
SC	-0.673	0.199	0.676	**1.000**	
SH	0.391	0.081	0.018	-0.204	**0.862**

Notes: PR = Perceived risk; PI = Personal innovativeness; RI = Revisit intention; SC = Service context; SH= Service heterogeneity. The bold number on the diagonal line represents the square root of AVE.

Variance inflation factors (VIF) values were computed to detect possible multicollinearity among the dependent and independent variables. All the VIF values are below the vigilance threshold of 5.0 [60]. Thus, multicollinearity is unlikely an issue for the proposed research model.

5.2 Test of the structural model

The structural model test involves estimating path coefficients, which indicate the power of the associations between the independent and dependent variables, and R^2 values, which indicate the amount of variance for the dependent variables explained by the independent variables. Taken together, the path coefficients (including both correlations and the significant level) and R^2 values demonstrate how well the data substantiate the hypothesized model.

Table 4 presents the results from the structural model analysis and substantiates all the hypothesized relationships. As postulated, customers' personal innovativeness negatively impacts perceived risk (β = -0.104; $p < 0.05$), supporting *H1*. Customers' perceived service heterogeneity contributes to increased perceived risk (β = 0.279; $p < 0.001$), confirming *H2*. Personal innovativeness, together with service heterogeneity, explains 60.4% of the variance in perceived risk. Perceived risk, in turn, negatively influences service revisit intention (β = -0.360; $p < 0.001$), explaining 58.4% of the variance in the revisit intention and consistent with *H3*.

To further test the mediating effects of perceived risk, we employ the approach prescribed by Nitzl et al. [61]. The first step is to verify the significance of the specific indirect relationship via the mediator. A significant result prompts the second step, which proceeds to test the direct relationship between the independent and dependent variables. If the direct relationship is insignificant, a full mediation can be concluded; otherwise, it is a partial mediation. As presented in Table 5, both specific indirect effects through the mediator are significant (PI: β = 0.045, $p < 0.05$; SH: β = -0.126, $p < 0.01$). Further, either personal innovativeness in robotic service (β = 0.133, $p < 0.01$) or service heterogeneity (β = 0.227, $p < 0.001$) has a significant direct negative influence on revisit intention. As a result, we can conclude that perceived risk partially mediates both the effects of personal innovativeness and service heterogeneity on service revisit intention.

Table 5. Results of Mediation Analysis

IV	IV → DV	IV → M→ DV	Mediation
PI	0.133^{**}	0.045^{*}	Partial
SH	0.227^{***}	-0.126^{**}	Partial

Notes: IV = Independent variable; M = Mediator; DV = Dependent variable. PI = Personal innovativeness; SH = Service heterogeneity. * correlation is significant at 0.05; ** correlation is significant at 0.01; *** correlation is significant at 0.001.

Service context works significantly as a moderator in the relationship between personal innovativeness in robotic service and perceived risk (β = -0.113; p < 0.05), therefore supporting *H4*. Specifically, the service context where a service robot worked well and satisfied the customer can strengthen the negative effect of personal innovativeness in robotic service on perceived risk. The relationship between service heterogeneity and perceived risk is also significantly moderated by whether the previous experience is satisfying (β = 0.271, p < 0.001), supporting *H5*. That is to say, the situation where the prior service experience satisfied customers can strengthen the positive effect of service heterogeneity on perceived risk.

Table 4. Results of Structural Equation Model Analysis

Effects	Estimate	t-vaue	Hypotheses test
Main effects			
Personal innovativeness → Perceived risk	-0.104^{*}	4.607	Supporting *H1*
Service heterogeneity → Perceived risk	0.279^{***}	4.344	Supporting *H2*
Perceived risk → Revisit intention	-0.360^{***}	6.258	Supporting *H3*
Interaction effects			
Personal innovativeness * service context → Perceived risk	-0.113^{*}	2.450	Supporting *H4*
Service heterogeneity * service context → Perceived risk	0.271^{***}	4.769	Supporting *H5*
Control effects			
House income → Revisit intention	-0.158^{*}	3.281	
Marital status → Revisit intention	0.167^{**}	2.820	
Child-bearing status → Revisit intention	$0.001^{n.s}$	0.016	
Gender → Revisit intention	$0.056^{n.s}$	1.086	
Age → Revisit intention	-0.103^{*}	1.968	
Education → Revisit intention	$0.028^{n.s.}$	0.597	
Service context → Perceived risk	-0.596^{***}	11.683	
Service context → Personal innovativeness	0.197^{**}	2.990	
Service context → Revisit intention	0.447^{***}	7.339	
Service context → service heterogeneity	-0.204^{**}	3.007	
Model statistics: R^2 (perceived risk) = 60.4%; R^2 (Revisit intention) = 58.4%.			

Notes: * correlation is significant at 0.05; ** correlation is significant at 0.01; *** correlation is significant at 0.001; $^{n.s.}$ correlation is not significant at 0.05.

6. Discussion and Implications

6.1 Interpretation of major results

Based on the major results of our research model, this study can help comprehensively understand customers' responding process to robotic service by explicating the roles of both customer trait and service characteristic in robotic service adoption.

First, personal innovativeness is negatively associated with customers' perceived risk in robotic service, leading to higher service revisit intention. This finding echoes previous studies that customer innovativeness plays a vital role in novel technology adoption and is critical for reducing customers' risk perception [19], [38]. Personal innovativeness reflects one's willingness to embrace innovations and ability to cope with uncertainties [36], [37]. Drawing from URT, it is feasible to mitigate customers' perceived risk in robotic service by promoting their innovativeness in robotic technologies.

Second, service heterogeneity is positively linked to customers' perceived risk, reducing their revisit intention to robotic service. Greater service heterogeneity indicates a higher possibility for the customer to receive discrepant services, equating to increased service performance uncertainty [25]. Such uncertainty can trigger customers' risk perception [26]. Our findings support the conclusion of Agudo-Peregrina et al. [28] that homogeneous service can decrease customers' perceived risk and further increase their purchase intention.

The mediation analysis manifests that perceived risk partially mediates the relationship between personal innovativeness/service heterogeneity and service revisit intention. In addition to the direct impacts of both personal innovativeness and service heterogeneity on service revisit intention, there also exist indirect effects through the mediator of perceived risk. Specifically, improving personal innovativeness can eventually boost customers' revisit intention as it can reduce service uncertainty and perceived risk through increasing personal risk-taking competence. Meanwhile, reducing service heterogeneity can ultimately improve customers' revisit intention since it decreases the possibility that customers receive differing services. These instrumental findings highlight the role of customers' perceived risk and indicate that decreasing customers' risk perception from the perspective of either customer or service characteristic has the potential to benefit service revisits.

Furthermore, the service context acts as a moderator in the relationship between personal innovativeness/service heterogeneity and perceived risk. Our results offer evidence that prior satisfying service alleviates the sense of risk in the next service visit. The satisfying service context can strengthen both the alleviating effect of personal innovativeness and the positive effect of service heterogeneity on risk perception.

6.2 Theoretical and practical implications

This study offers several implications on the theoretical front. First, despite that the dominant technology acceptance models provide insights into the formation of adoption intention [16], [17], this study contributes to further the understanding of robotic service adoption by clarifying the roles of both customer and service characteristics in AI technology adoption. Notably, identifying the critical service characteristic, i.e., service heterogeneity, conduces to a powerful instrument for future research that employs service heterogeneity as a theoretical lens to investigate robotic service. This study also enriches the existing literature and facilitates future empirical studies by systematically developing and verifying service heterogeneity measurements. While numerous researchers in the service science suggest that heterogeneity in service leads to adverse influences on customers' satisfaction yet without empirical support [62], [63], this study empirically shows that service heterogeneity significantly affects customers' service revisit intention directly and indirectly through the partial mediator of perceived risk.

Second, this study is among the first to employ URT to explain how customers respond to and adopt robotic service. Although past studies have confirmed the significance of personal innovativeness in technology adoption [18], [19] and argued negative implications of service heterogeneity on customer experience [10], this study focuses more on the mediating effect of perceived risk in the relationship between individual innovativeness/service heterogeneity and customers' revisit intention. Conceptualizing both customer and service characteristics, perceived risk, and service revisit intention within the URT framework offers a sharper theoretical lens to understand the mechanism of robotic service adoption.

The third contribution of our study is extending personal innovativeness and service heterogeneity by delineating the service context's influence. Specifically, the suppression of customers' risk perception by personal innovativeness can be strengthened in the satisfying service context. More importantly, this study empirically shows that the effect of service heterogeneity on customers' perceived risk differs after experiencing a satisfying as opposed to dissatisfying service. Our findings emphasize the importance of customers' initial interaction experience with service robots.

This study also conveys several practical implications. First, with robot attendants springing up into the service realm, practitioners need to realize the significance of promoting customers' innovativeness in increasing service revisits. Second, on the operational side of service robots, more attention should be paid to decreasing customers' risk perception and chewing over uncertainty reduction strategies. Third, service operators need to recognize the importance of simultaneously improving customers' initial experience with service robots and reducing robotic service heterogeneity.

Limitations still exist in the current study, which warrants further investigation. First, considering that this study utilized a scenario-based experiment with manipulated service contexts, a prospective study in the real-world setting is recommended to supply this research domain. Second, our study focused on customer trait, service characteristic, and perceived risk, a more comprehensive investigation is needed to address other constructs, such as comfort with robots and trust in robotic service.

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