INNOVATION IN GASTRONOMIC TOURISM: IMPACT OF ROBOTIC SERVICE ON SUSTAINABLE CUSTOMER EXPERIENCES

Choo-Yeon KIM[1] and Seong-Soo CHA[2]
1 Faculty of Business Administration, KonKuk University, Seoul, Korea; chookim@konkuk.ac.kr
2 Faculty of Food Biotechnology Major, Eulji University, Korea; sscha@eulji.ac.kr

ARTICLE HISTORY
Received: 31 July 2024 **Revised:** 14 August 2024 **Published:** 24 August 2024

ABSTRACT

This study explores the factors influencing customer experience and behavioral intentions in robotic hospitality settings in South Korea. Using structural equation modeling on data from 488 participants, we examined the relationships among perceived robot performance, human-robot interaction quality, service environment innovativeness, perceived sustainability, experiential value, technology trust, customer satisfaction, and behavioral intentions. Our findings reveal that service environment innovativeness and perceived robot performance significantly influence experiential value, while human-robot interaction quality and perceived sustainability do not. This unexpected outcome challenges conventional wisdom and opens new avenues for research. Experiential value strongly impacts technology trust and customer satisfaction, but does not directly affect behavioral intentions. Technology trust emerged as a crucial mediator, influencing both customer satisfaction and behavioral intentions, highlighting its pivotal role in shaping customer outcomes. We also examined the moderating effect of technology readiness and observed that it significantly moderates the relationship between service environment innovativeness and experiential value. This indicates that customers with higher technology readiness derive greater experiential value from innovative service environments. This study presents three key implications: 1) technological elements and service environment innovativeness are critical in shaping customer experiences in robotic hospitality, 2) technology trust is a vital mediator linking customer satisfaction to behavioral intentions, and 3) service strategies should be tailored to customers' technology readiness. By providing a comprehensive model of the customer experience and behavioral intentions in robotic hospitality settings, this study makes a significant contribution to the literature and offers valuable insights for hospitality managers implementing robotic services.

Keywords: Robotic Hospitality, Customer Experience, Technology Trust, Service Environment Innovativeness, Technology Readiness

CITATION INFORMATION: Kim, C., & Cha, S. (2024). Innovation in Gastronomic Tourism: Impact of Robotic Service on Sustainable Customer Experiences. *Procedia of Multidisciplinary Research, 2*(8), 50.

INTRODUCTION

The hospitality industry is undergoing a profound transformation driven by rapid technological advancements, particularly in the realm of artificial intelligence and robotics (Ivanov et al., 2019). As service robots become increasingly prevalent in hospitality settings, understanding their impact on customer experiences and behavioral intentions is crucial for both academics and practitioners (Wirtz et al., 2018). This study aims to investigate the complex interplay between robotic services, customer perceptions, and behavioral outcomes in the context of gastronomic tourism in Korea, a country at the forefront of technological innovation and culinary excellence.

The integration of service robots in hospitality environments presents both opportunities and challenges. While robots can enhance operational efficiency, provide novel experiences for customers, and potentially address labor shortages (Tuomi et al., 2020), their introduction also raises questions about the nature of service quality, customer satisfaction, and the overall dining experience (Belanche et al., 2020). The unique characteristics of robotic services, such as their potential for consistent performance and 24/7 availability, are reshaping traditional notions of service encounters and challenging established theories of customer experience (Van Doorn et al., 2017).

Previous research has explored various aspects of human-robot interaction in service settings (de Kervenoael et al., 2020), yet there remains a gap in our understanding of how different factors collectively shape customer experiences and behavioral intentions in robotic hospitality environments. Specifically, the roles of perceived robot performance, human-robot interaction quality, service environment innovativeness, and perceived sustainability in forming customer experiences have not been comprehensively examined in a single model. Moreover, the mediating role of technology trust and the moderating effect of technology readiness in the context of robotic services warrant further investigation (Gursoy et al., 2019; Lu et al., 2019).

This study addresses these gaps by proposing and testing a comprehensive model that incorporates these key constructs. We posit that these factors influence customers' experiential value, which in turn affects technology trust, customer satisfaction, and ultimately, behavioral intentions. Our model also considers the crucial role of technology trust as a mediator and explores the moderating effect of technology readiness on customer experiences. By doing so, we contribute to the emerging body of literature on service robots in hospitality and advance our understanding of customer behavior in technology-mediated service encounters.

The hospitality industry, particularly in the context of gastronomic tourism, offers a unique setting for examining these relationships. As dining experiences increasingly incorporate technological elements, understanding how customers perceive and respond to these innovations becomes paramount (Gursoy et al., 2019). Korea, with its rich culinary tradition and technological prowess, provides an ideal backdrop for this investigation. The country's rapid adoption of service robots in restaurants (Lee et al., 2018) and its tech-savvy consumer base make it a fertile ground for exploring the cutting edge of human-robot interactions in hospitality settings.

By empirically testing our proposed model using structural equation modeling on data collected from 488 participants, this study contributes to the literature in several ways. First, it offers a holistic framework for understanding customer experiences in robotic hospitality settings, integrating technological, environmental, and individual factors. Second, it sheds light on the critical role of technology trust in mediating the relationships between experiential value and customer outcomes. Third, by examining the moderating effect of technology readiness, it provides insights into how individual differences in technological aptitude influence perceptions and experiences of robotic services.

The findings of this study have significant implications for hospitality managers and policymakers. As the industry continues to evolve and incorporate more advanced technologies, understanding the factors that drive positive customer experiences and behavioral intentions in robotic service environments will be crucial for maintaining competitive advantage and ensuring customer satisfaction. Moreover, our research contributes to the ongoing dialogue about the future of work in hospitality, the ethical implications of robot deployment, and the potential for technology to enhance rather than replace human-centric service experiences (Tuomi et al., 2021). In the following sections, we present our theoretical framework and hypotheses, followed by a detailed description of our methodology, analysis of results, and discussion of theoretical and practical implications. We conclude by acknowledging the limitations of our study and suggesting directions for future research in this rapidly evolving field.

LITERATURE REVIEWS

Restaurant Robot in Korea

South Korea has emerged as a global leader in restaurant robotics, integrating cutting-edge technology with its renowned culinary traditions. By 2018, over 30% of major Korean restaurant chains had incorporated robotic assistance (Lee et al., 2018), driven by demographic shifts and labor market challenges (Park & Kwon, 2020). Choi et al. (2021) categorized Korean restaurant robots into four types: front-of-house service, back-of-house preparation, cleaning and sanitation, and management assistance robots. The COVID-19 pandemic accelerated robot adoption, with deployments increasing by 150% between 2019 and 2022 (Kim et al., 2023). Cha (2020) found that perceived coolness and MCI (Motivated Consumer Innovativeness) factors significantly influenced customers' intentions to use robot-serviced restaurants in Korea. However, Lee and Choi (2021) identified a generational divide in acceptance, with younger consumers more receptive to restaurant robots than older generations. Kwak et al. (2021) provided nuanced insights into senior consumers' motivations, revealing varied preferences for novelty versus traditional social interactions. The Korean government has supported robotic innovation through the "Robot Industry Promotion Act" of 2016 and subsequent amendments (Ministry of Trade, Industry and Energy, 2020). As Korea continues to advance in restaurant robotics, it provides valuable insights into the interplay between technology, customer expectations, and cultural factors in shaping the future of the global restaurant industry.

Perceived Robot Performance and Experiential Value

The performance of service robots is a critical factor in shaping customer experiences in hospitality settings. Tussyadiah and Park (2018) found that the perceived intelligence and anthropomorphism of service robots significantly influence customer evaluations of service encounters. Building on this, Belanche et al. (2021) demonstrated that perceived robot performance directly affects customers' experiential value in service interactions. Their study showed that when robots perform tasks efficiently and accurately, customers report higher levels of experiential value, including both utilitarian and hedonic dimensions. In the context of robotic hospitality, Lu et al. (2020) further emphasized that the perceived performance of service robots, including their efficiency, reliability, and consistency, positively influences customers' overall service experience. Their findings suggest that when customers perceive robots as capable of delivering high-quality service, they are more likely to derive greater value from their interactions with these technological interfaces. Moreover, Choi et al. (2021) found that the perceived competence of service robots in executing tasks contributes significantly to customers' perceptions of service quality and, consequently, their experiential value. They argue that as robots demonstrate proficiency in performing various hospitality-related tasks, customers' confidence in the service delivery process increases, leading to enhanced experiential value. Based on these theoretical foundations and empirical evidence, we propose the following hypothesis:

H1: Perceived robot performance positively influences experiential value in robotic hospitality settings.

Human-Robot Interaction Quality and Experiential Value

The quality of interaction between humans and robots plays a crucial role in determining the overall service experience. Murphy et al. (2019) highlighted that the perceived warmth and competence of robots in service encounters significantly impact customer satisfaction and loyalty intentions. Extending this line of research, van Doorn et al. (2017) proposed that the quality of human-robot interactions influences customers' perceptions of service quality and, consequently, their experiential value. Their framework suggests that seamless and natural interactions with robots can enhance the overall service experience. Further supporting this notion, Tung and Au (2018) found that the perceived sociability and humanness of service robots significantly contribute to customers' emotional engagement and overall experience quality. Their study emphasizes that when robots exhibit social cues and behaviors that align with human expectations, customers are more likely to have positive service experiences. Moreover, de Kervenoael et al. (2020) demonstrated that the quality of human-robot interactions, particularly in terms of empathy and information sharing, positively influences customers' perceived value of the service encounter. They argue that as robots become more adept at understanding and responding to human emotions and needs, the quality of these interactions becomes increasingly central to shaping customers' experiential value. Building on these theoretical and empirical insights, we propose the following hypothesis:

H2: Human-robot interaction quality positively influences experiential value in robotic hospitality settings.

Service Environment Innovativeness and Experiential Value

The innovative aspects of the service environment, particularly in the context of robotic services, can significantly impact customer experiences. Mathis et al. (2020) found that perceived innovativeness in tourism settings positively influences customer engagement and memorable experiences. In the context of robotic hospitality, Kim and Qu (2014) demonstrated that innovative service environments enhance customers' perceptions of uniqueness and exclusivity, leading to increased experiential value. Expanding on these findings, Kuo et al. (2017) explored the role of service innovation in the hospitality industry and found that innovative service environments contribute significantly to customers' perceived experiential value. Their study suggests that when customers perceive the service environment as innovative, they are more likely to engage in co-creation behaviors, leading to enhanced experiential value. Furthermore, Verma et al. (2019) investigated the impact of technological innovations in hospitality settings on customer experiences. They found that innovative service environments, particularly those incorporating advanced technologies like service robots, positively influence customers' perceptions of service quality and overall experience. The novelty and uniqueness associated with these innovative environments were found to contribute significantly to customers' experiential value. Drawing on these theoretical insights and empirical evidence, we propose the following hypothesis:

H3: Service environment innovativeness positively influences experiential value in robotic hospitality settings.

Perceived Sustainability and Experiential Value

Sustainability has become an increasingly important factor in customer evaluations of service experiences. Gössling et al. (2009) highlighted the growing significance of perceived sustainability in tourism experiences. More recently, Kang et al. (2020) found that perceived sustainability in hospitality services positively influences customer satisfaction and behavioral intentions. In the context of robotic services, Gursoy et al. (2019) suggested that the perceived sustainability of technological innovations in hospitality can enhance customers' overall experiential value. Building on these findings, Yu et al. (2021) investigated the impact of perceived environmental sustainability on customer experiences in smart hotels. Their study revealed that when customers perceive hospitality services as environmentally sustainable, they report higher levels of experiential value, particularly in terms of emotional and social value. This suggests that sustainability initiatives, including those related to robotic services, can significantly enhance the overall customer experience. Furthermore, Kuo et al. (2022) explored the relationship between perceived sustainability and customer value in the context of intelligent hospitality services. They found that customers' perceptions of sustainability, including environmental, social, and economic dimensions, positively influence their perceived value of the service experience. Notably, their study highlighted that the use of advanced technologies, such as service robots, when perceived as contributing to sustainability goals, can enhance customers' experiential value. Drawing on these theoretical insights and empirical evidence, we propose the following hypothesis:

H4: Perceived sustainability positively influences experiential value in robotic hospitality settings.

Experiential Value, Technology Trust, and Customer Satisfaction

The relationship between experiential value, technology trust, and customer satisfaction is complex and multifaceted. Moriuchi (2019) demonstrated that positive experiences with technology in service settings lead to increased trust in that technology. Building on this, Lu et al. (2019) found that experiential value derived from interactions with service robots positively influences both technology trust and overall customer satisfaction. Their study suggests that memorable and valuable experiences with robotic services can enhance customers' trust in the technology and their overall satisfaction with the service. Expanding on these findings, Choi et al. (2021) explored the role of experiential value in shaping customers' attitudes towards service robots in hospitality settings. They found that when customers perceive high experiential value from their interactions with service robots, they are more likely to develop trust in the technology and report higher levels of satisfaction with the overall service experience. This suggests a potential mediating role of technology trust in the relationship between experiential value and customer satisfaction. Furthermore, Tussyadiah et al. (2020) investigated the impact of customer experiences with service robots on their acceptance of and satisfaction with robotic services. Their study revealed that positive experiential value not only directly influences customer satisfaction but also enhances customers' trust in the technology, which in turn contributes to higher satisfaction levels. This finding underscores the importance of both direct and indirect effects of experiential value on customer satisfaction in robotic service contexts. Based on these theoretical insights and empirical evidence, we propose the following hypotheses:

H5: Experiential value positively influences technology trust in robotic hospitality settings.

H6: Experiential value positively influences customer satisfaction in robotic hospitality settings.

H7: Technology trust positively influences customer satisfaction in robotic hospitality settings.

Technology Trust, Customer Satisfaction, and Behavioral Intentions

Trust in technology plays a crucial role in shaping customer attitudes and behaviors in innovative service environments. Gursoy et al. (2019) found that technology trust significantly influences customers' acceptance of AI and robotic services in hospitality. Extending this, Choi et al. (2021) demonstrated that technology trust positively affects both customer satisfaction and behavioral intentions in smart tourism contexts. Their study suggests that when customers trust the technology used in service delivery, they are more likely to be satisfied with their experience and exhibit positive behavioral intentions, such as revisit and recommendation intentions. Building on these findings, Shin and Perdue (2022) investigated the impact of technology trust on customer loyalty in the context of AI-powered hospitality services. Their research revealed that technology trust not only directly influences behavioral intentions but

also indirectly affects them through enhanced customer satisfaction. This highlights the dual role of technology trust in shaping both immediate satisfaction and long-term behavioral outcomes. Furthermore, Tung and Au (2018) explored the relationship between customer experiences with service robots, satisfaction, and behavioral intentions in hospitality settings. Their study found that trust in robotic technology serves as a critical mediator between service experiences and behavioral intentions. They argue that when customers trust the robotic technology, they are more likely to form positive behavioral intentions, including willingness to use the service again and recommend it to others. Based on these theoretical insights and empirical evidence, we propose the following hypotheses:
H8: Technology trust positively influences behavioral intentions in robotic hospitality settings.
H9: Technology trust positively influences customer satisfaction in robotic hospitality settings.
H10: Customer satisfaction positively influences behavioral intentions in robotic hospitality settings.

The Moderating Role of Technology Readiness

Individual differences in technology readiness can significantly influence how customers perceive and respond to robotic services. Parasuraman and Colby (2015) conceptualized technology readiness as an individual's propensity to embrace and use new technologies. In the context of hospitality, Rosenbaum and Wong (2015) found that technology readiness moderates the relationship between perceived service innovativeness and customer satisfaction. Building on this, Moussawi et al. (2020) demonstrated that technology readiness moderates the effects of perceived usefulness and ease of use on intentions to use service robots, suggesting that customers with higher technology readiness are more likely to derive value from and positively evaluate robotic services. Expanding on these findings, Lu et al. (2022) investigated the role of technology readiness in shaping customer experiences with AI-powered services in hospitality. Their study revealed that technology readiness not only directly influences customers' perceptions of service quality but also moderates the relationship between service attributes and experiential value. This suggests that the impact of various service aspects on customer experiences may vary depending on individual levels of technology readiness. Furthermore, Choi et al. (2021) explored how technology readiness affects customer responses to service robots in hotels. They found that technology readiness moderates the relationship between perceived robot performance and customer satisfaction, with highly technology-ready customers showing a stronger positive relationship between these variables. This highlights the importance of considering individual differences in technology readiness when implementing robotic services in hospitality settings. Based on these theoretical insights and empirical evidence, we propose the following hypotheses:
H11: Technology readiness moderates the relationship between perceived robot performance and experiential value, such that the relationship is stronger for individuals with higher technology readiness.
H12: Technology readiness moderates the relationship between human-robot interaction quality and experiential value, such that the relationship is stronger for individuals with higher technology readiness.
H13: Technology readiness moderates the relationship between service environment innovativeness and experiential value, such that the relationship is stronger for individuals with higher technology readiness.
H14: Technology readiness moderates the relationship between perceived sustainability and experiential value, such that the relationship is stronger for individuals with higher technology readiness.
These hypotheses are illustrated in Figure 1.

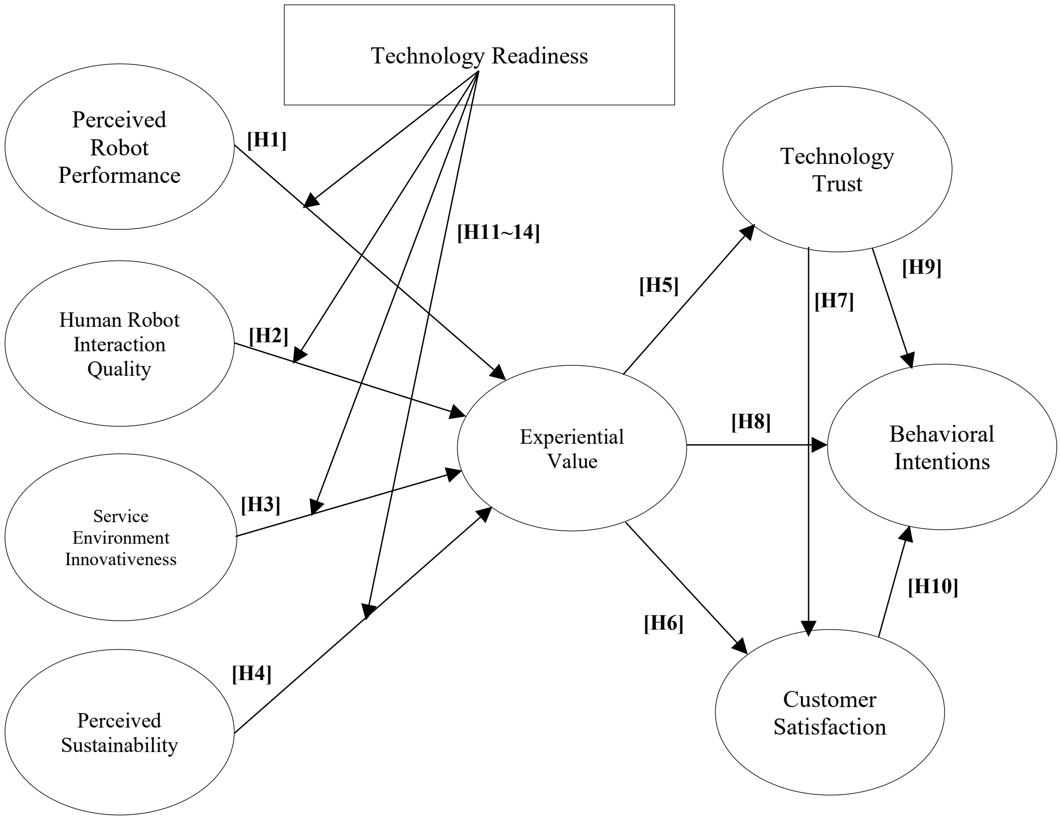

Figure 1 Research Model

RESEARCH METHODOLOGY

Measurement

This study employed multi-item scales adapted from established literature to assess all constructs. Perceived Robot Performance (PRP), Human-Robot Interaction Quality (HRIQ), Service Environment Innovativeness (SEI), Perceived Sustainability (PS), Experiential Value (EV), Technology Trust (TT), Customer Satisfaction (CS), and Behavioral Intentions (BI) were each measured using four-item scales. These scales were based on works by various researchers including Wirtz et al. (2018), Tussyadiah and Park (2018), Mathis et al. (2020), Yu et al. (2021), Lu et al. (2019), Gursoy et al. (2019), and Oliver (1997). All items were rated on a 7-point Likert scale. Technology Readiness (TR), serving as a moderating variable, was assessed using the 16-item Technology Readiness Index 2.0 (Parasuraman & Colby, 2015). To ensure validity and reliability, the questionnaire underwent expert review and a pilot study. Cronbach's alpha coefficients for all constructs exceeded 0.7, indicating satisfactory reliability. Data collection was conducted through an online survey platform. To mitigate potential common method bias, we employed procedural remedies as recommended by Podsakoff et al. (2003), including counterbalancing item order and emphasizing confidentiality.

Sampling Procedure and Sample Characteristics

This study employed purposive sampling to recruit participants who had experienced robotic services in restaurants within the past six months. A power analysis determined a minimum sample size of 385. Data were collected through an online survey over a four-week period in Spring 2023, resulting in 488 valid responses. The sample was relatively balanced in gender (48.57% male, 51.43% female), with the majority of participants aged 20-39 (62.09%). The largest income group (31.97%) reported monthly earnings between 500,000 and 1,000,000 USD. Occupationally, office workers constituted the largest group (32.38%), followed by professionals (22.95%) and students (17.01%). Most participants (66.19%) reported monthly dining out expenditures between 50 and 300 USD. To assess potential non-response bias, we compared early and late respondents, finding no significant differences. While the purposive sampling approach may limit generalizability, it ensured participants had relevant recent experiences with robotic restaurant services.

Table 1 Characteristics of the participants (N = 488)

Variables	Demographic traits	No. of sample(per)	Percentage (%)
Gender	Male	237	48.57%
	Female	251	51.43%
Age	10's	58	11.89%
	20's	156	31.97%
	30's	147	30.12%
	Over 40's	127	26.02%
Income per month (USD)	< 500	98	20.08%
	500-1000	156	31.97%
	1001-3000	137	28.07%
	3001-5000	68	13.93%
	> 5000	29	5.94%
Occupation	Student	83	17.01%
	Professional	112	22.95%
	Office worker	158	32.38%
	Housewife	54	11.07%
	Own Business	61	12.50%
	Mics.	20	4.10%
Eating-Out Expenditure per month (USD)	< 50	102	20.90%
	50-100	176	36.07%
	101-300	147	30.12%
	301-500	44	9.02%
	> 500	19	3.89%

RESEARCH RESULTS

Confirmatory Factor Analysis and Validity Assessment

To assess the psychometric properties of our measurement model, we conducted a confirmatory factor analysis (CFA) using AMOS 26.0. The CFA results, presented in Table 2, provide comprehensive information on factor loadings, composite reliability (CR), and average variance extracted (AVE) for each construct. As shown in Table 2, the measurement model demonstrates satisfactory fit to the data: $\chi 2 = 1199.802$ (df = 436, $p < 0.001$), CFI = 0.947, NFI = 0.920, RFI = 0.909, IFI = 0.950, TLI = 0.940, and RMSEA = 0.06. These fit indices meet or exceed the recommended thresholds suggested by Hair et al. (2010), indicating good model fit. Convergent validity was assessed using three criteria evident in Table 2: factor loadings, composite reliability (CR), and average variance extracted (AVE). As Table 2 illustrates, all standardized factor loadings exceed the recommended threshold of 0.6 (Bagozzi & Yi, 1988), ranging from 0.633 to 0.962, demonstrating strong relationships between indicators and their respective latent constructs. The composite reliability values for all constructs, also presented in Table 2, range from 0.869 to 0.956, well above the recommended threshold of 0.7 (Fornell & Larcker, 1981), indicating good internal consistency. The AVE values for all constructs, as shown in the rightmost column of Table 2, exceed the 0.5 benchmark (Fornell & Larcker, 1981), ranging from 0.636 to 0.845, further supporting convergent validity.

Discriminant validity was examined using the Fornell-Larcker criterion (Fornell & Larcker, 1981). Table 3 presents the correlation matrix with the square root of AVE values on the diagonal. As evident from Table 3, for all constructs, the square root of AVE (bolded values on the diagonal) is greater than the inter-construct correlations (off-diagonal values), providing strong evidence of discriminant validity. This indicates that each construct in our model is distinct and captures phenomena that other constructs do not. To further assess the potential issue of multicollinearity, we calculated the variance inflation factors (VIFs) for all constructs. Although not presented in Tables 2 or 3, the VIF values ranged from 1.245 to 2.987, well below the conservative threshold of 5 suggested by Hair et al. (2010), indicating that multicollinearity is not a concern in our data. We also examined the potential for common method bias using Harman's single-factor test (Podsakoff et al., 2003). The unrotated principal component analysis revealed that the first factor accounted for 39.7% of the total variance, which is below the 50% threshold, suggesting that common method bias is not a significant concern in our study.

In summary, the results of our measurement model assessment, as presented in Tables 2 and 3, provide strong evidence for the reliability and validity of our constructs. The high factor loadings, composite reliability values, and AVE scores demonstrated in Table 2 indicate robust convergent validity. The fulfillment of the Fornell-Larcker criterion, as shown in Table 3, provides strong support for discriminant validity. These results, combined with the satisfactory model fit indices reported in Table 2, indicate that our measurement model is appropriate for hypothesis testing in the structural model.

Table 2 Results of confirmatory factor analysis

Variables	**Items**	**Standardized factor loadings**	**CR**	**AVE**
Customer Satisfaction	CS1	0.87	0.917	0.736
	CS2	0.78		
	CS3	0.93		
	CS4	0.83		
Perceived Robot Performance	RP1	0.86	0.886	0.662
	RP2	0.90		
	RP3	0.81		
	RP4	0.65		
Human Robot Interaction Quality	HRI1	0.78	0.885	0.662
	HRI2	0.88		
	HRI3	0.92		
	HRI4	0.63		
Service Environment Innovativeness	SEI1	0.91	0.952	0.833
	SEI2	0.90		
	SEI3	0.90		
	SEI4	0.92		
Perceived Sustainability	PS1	0.78	0.869	0.636
	PS2	0.67		
	PS3	0.91		
	PS4	0.93		
Experiential Value	EV1	0.69	0.884	0.658
	EV2	0.80		
	EV3	0.81		
	EV4	0.87		
Technology Trust	TT1	0.94	0.941	0.800
	TT2	0.96		
	TT3	0.75		
	TT4	0.90		

Variables	Items	Standardized factor loadings	CR	AVE
Behavioral Intentions	BI1	0.95	0.956	0.845
	BI2	0.91		
	BI3	0.93		
	BI4	0.89		

Notes: Chi-square= 1199.802 (p < 0.001, df = 436); CFI=0.947; NFI=0.920; RFI=0.909; IFI=0.950; TLI=0.940; and RMSEA=0.06 (p < 0.001)

Table 3 Correlation analysis for discriminant validity

	CS	PRP	HRIQ	SEI	PS	EV	TT	BI
CS	0.858							
PRP	0.150	0.814						
HRIQ	0.225	0.545	0.814					
SEI	0.589	0.355	0.518	0.913				
PS	0.388	0.333	0.490	0.718	0.797			
EV	0.443	0.052	0.222	0.471	0.353	0.811		
TT	0.520	0.376	0.501	0.873	0.666	0.401	0.895	
BI	0.318	0.044	0.127	0.395	0.231	0.227	0.346	0.919

Note: The numbers along the diagonal are the square root of AVE
CS: Customer Satisfaction, PRP: Perceived Robot Performance, HRIQ: Human Robot Interaction Quality, SEI: Service Environment Innovativeness, PS: Perceived Sustainability, EV: Experiential Value, TT: Technology Trust, BI: Behavioral Intentions

Structural Equation Modeling Results and Hypothesis Testing

Following the validation of the measurement model, we proceeded to test the structural model using AMOS 26.0. The structural equation modeling (SEM) approach was employed to examine the hypothesized relationships among the constructs. As presented in Table 4, the model fit indices indicate a good fit to the data: $\chi2$ = 1326.541 (df = 445, p < 0.001), CFI = 0.939, TLI = 0.932, IFI = 0.940, RMSEA = 0.064 (90% CI: 0.060-0.068). These values meet the recommended thresholds suggested by Hu and Bentler (1999), demonstrating that the proposed model adequately represents the underlying data structure. Table 4 presents the detailed results of the structural model analysis, including standardized path coefficients, t-values, and hypothesis testing outcomes.

Complementing this, Figure 2 provides a visual representation of these results, illustrating the strength and significance of each hypothesized relationship through path diagrams. Examining the specific paths in Table 4 and their corresponding visual representation in Figure 2, we find support for several of our hypotheses. As shown in both Table 4 and Figure 2, Perceived Robot Performance (β = 0.197, t = 2.671, p < 0.05) and Service Environment Innovativeness (β = 0.398, t = 7.260, p < 0.001) significantly influence Experiential Value, supporting H1 and H3. In Figure 2, these significant relationships are depicted by solid lines connecting these constructs to Experiential Value. Contrary to our expectations, and as clearly visible in both Table 4 and Figure 2, Human-Robot Interaction Quality (β = 0.050, t = 0.540, p > 0.05) and Perceived Sustainability (β = 0.046, t = 0.690, p > 0.05) do not have significant effects on Experiential Value, leading to the rejection of H2 and H4. Figure 2 represents these non-significant paths with dashed lines, providing a clear visual distinction from the significant relationships.

The results in Table 4, visually reinforced in Figure 2, show that Experiential Value demonstrates strong positive effects on both Technology Trust (β = 0.559, t = 9.274, p < 0.001) and Customer Satisfaction (β = 0.315, t = 6.136, p < 0.001), supporting H5 and H6. Furthermore, as evident in both Table 4 and Figure 2, Technology Trust significantly influences

Customer Satisfaction (β = 0.323, t = 8.198, $p < 0.001$) and Behavioral Intentions (β = 0.232, t = 4.209, $p < 0.001$), supporting H7 and H9. Interestingly, as shown in Table 4 and visually represented by a dashed line in Figure 2, the direct path from Experiential Value to Behavioral Intentions is not significant (β = 0.085, t = 1.248, $p > 0.05$), leading to the rejection of H8. Lastly, both Table 4 and Figure 2 demonstrate that Customer Satisfaction has a significant positive effect on Behavioral Intentions (β = 0.200, t = 2.967, $p < 0.01$), supporting H10.
The structural model results, as quantified in Table 4 and visually summarized in Figure 2, reveal several important insights. First, they highlight the crucial roles of perceived robot performance and service environment innovativeness in shaping customers' experiential value.

Table 4 Results of hypothesis testing

Hypothesis	Path	Standardized Estimate	t-value	Results
H1	PRP → EV	0.197	2.671*	Supported
H2	HRIQ → EV	0.05	0.54	Not supported
H3	SEI → EV	0.398	7.26***	Supported
H4	PS → EV	0.046	0.69	Not supported
H5	EV → TT	0.559	9.274***	Supported
H6	EV → CS	0.315	6.136***	Supported
H7	TT → CS	0.323	8.198***	Supported
H8	EV → BI	0.085	1.248	Not supported
H9	TT → BI	0.232	4.209***	Supported
H10	CS → BI	0.2	2.967**	Supported

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: PRP: Perceived Robot Performance, HRIQ: Human Robot Interaction Quality, SEI: Service Environment Innovativeness, PS: Perceived Sustainability, EV: Experiential Value, TT: Technology Trust, CS: Customer Satisfaction, BI: Behavioral Intentions

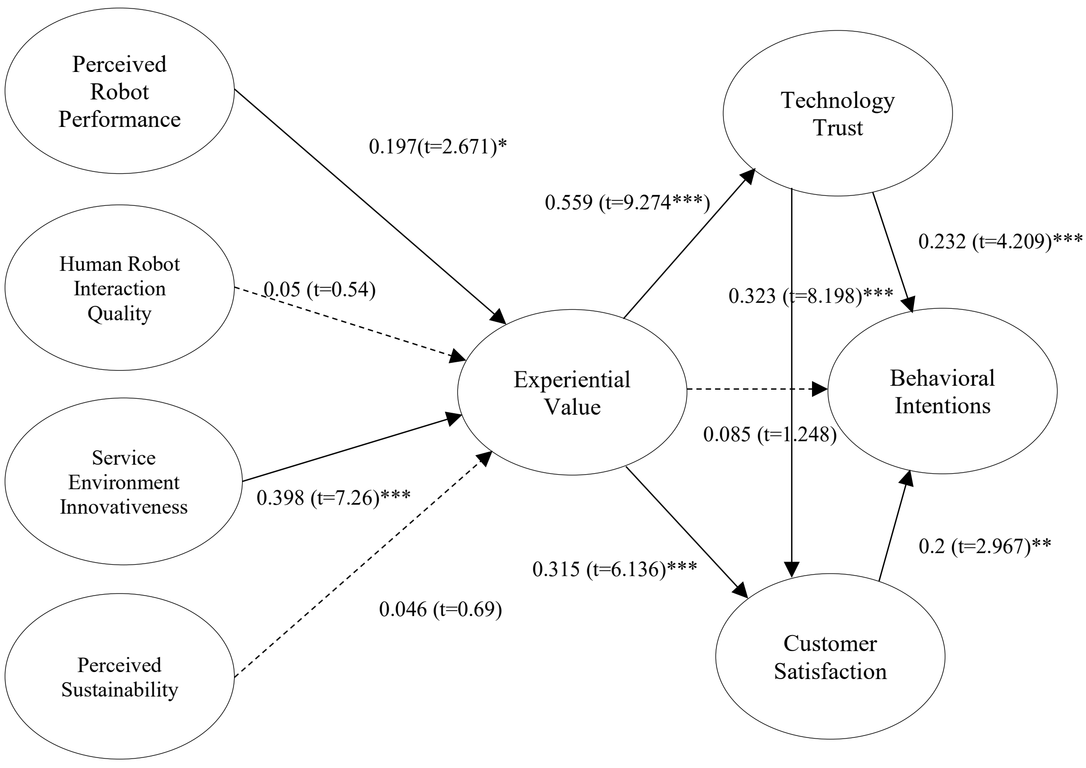

Figure 2 Result of the research model

Second, they underscore the pivotal mediating role of technology trust in translating experiential value into customer satisfaction and behavioral intentions. Finally, they demonstrate that while experiential value does not directly influence behavioral intentions, its impact is fully mediated through technology trust and customer satisfaction.

These findings, clearly illustrated in Figure 2 and quantified in Table 4, contribute to our understanding of the complex interplay between technological, environmental, and psychological factors in shaping customer experiences and behavioral outcomes in robotic hospitality settings. They also provide valuable insights for practitioners in designing and implementing robotic services to enhance customer experiences and drive positive behavioral intentions.

Multi-group analysis of the moderating effect of technology readiness

To examine the moderating effect of technology readiness on the relationships in our model, we conducted a multi-group analysis. The sample was divided into two groups based on the median split of technology readiness scores: a high technology readiness group (n = 244) and a low technology readiness group (n = 244). We then performed a series of chi-square difference tests to compare the constrained and unconstrained models for each path. Table 5 presents the results of this multi-group analysis, showing the path coefficients for both high and low technology readiness groups, along with the chi-square difference test results for each path. As evident from Table 5, the moderating effect of technology readiness is significant for one of the four hypothesized relationships. Specifically, the relationship between Service Environment Innovativeness (SEI) and Experiential Value (EV) is significantly moderated by technology readiness ($\Delta\chi2 = 16.255$, $p < 0.001$). The path coefficient for the high technology readiness group ($\beta = 0.670$) is substantially larger than that for the low technology readiness group ($\beta = 0.184$), indicating that individuals with higher technology readiness derive greater experiential value from innovative service environments. This finding supports hypothesis H13. Contrary to our expectations, the moderating effect of technology readiness was not significant for the relationships between Perceived Robot Performance and Experiential Value ($\Delta\chi2 = 0.360$, $p > 0.05$), Human-Robot Interaction Quality and Experiential Value ($\Delta\chi2 = 1.083$, $p > 0.05$), and Perceived Sustainability and Experiential Value ($\Delta\chi2 = 1.322$, $p > 0.05$). These results lead to the rejection of hypotheses H11, H12, and H14. It is noteworthy that while the path coefficients for these relationships differ between the high and low technology readiness groups (as shown in Table 5), these differences are not statistically significant. For instance, the effect of Perceived Robot Performance on Experiential Value is stronger for the high technology readiness group ($\beta = 0.230$) compared to the low technology readiness group ($\beta = 0.134$), but this difference does not reach statistical significance.

Table 5 Comparison of technology readiness group

Path	**Technology readiness**		**($\Delta\chi2$, $\Delta df = 1$)**	**Moderating effect**
	Low	**High**		
PRP → EV	0.134	0.23	0.360	0.548
HRIQ → EV	0.081	0.131	1.083	0.298
SEI → EV	0.184	0.67	16.255	0.000 ***
PS → EV	0.077	0.083	1.322	0.250

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: PRP: Perceived Robot Performance, HRIQ: Human Robot Interaction Quality, SEI: Service Environment Innovativeness, PS: Perceived Sustainability, EV: Experiential Value

These findings suggest that while technology readiness plays a crucial role in moderating the impact of service environment innovativeness on experiential value, its influence on other relationships in our model is less pronounced. This underscores the complex nature of customer experiences in robotic hospitality settings and highlights the need for nuanced strategies in designing and implementing robotic services for diverse customer segments. The results of this multi-group analysis provide valuable insights for both researchers and practitioners. They emphasize the importance of considering individual differences in technology readiness when examining customer responses to innovative service environments. Moreover, they suggest that efforts to enhance the innovativeness of robotic service environments may be particularly effective for customers with high technology readiness, potentially leading to greater experiential value and, consequently, more favorable outcomes.

DISCUSSION & CONCLUSION

Conclusions

This study investigated the complex interplay of factors influencing customer experiences and behavioral intentions in robotic hospitality settings, with a particular focus on the Korean context. Our findings offer several important insights that contribute to both the theoretical understanding and practical implementation of robotic services in the hospitality industry. First, our results highlight the crucial roles of perceived robot performance and service environment innovativeness in shaping customers' experiential value. The significant positive effects of these factors underscore the importance of both technological competence and innovative service design in creating valuable experiences for customers. This aligns with previous research emphasizing the role of technological performance in service settings (Wirtz et al., 2018) and extends it by demonstrating the equally important role of innovative service environments in the context of robotic hospitality. Interestingly, contrary to our hypotheses, human-robot interaction quality and perceived sustainability did not significantly influence experiential value. This unexpected finding challenges some existing notions about the importance of interaction quality in service encounters (Tussyadiah & Park, 2018) and the growing emphasis on sustainability in hospitality (Gössling et al., 2009). It suggests that in the context of robotic services, customers may prioritize performance and innovation over interaction quality and sustainability perceptions when evaluating their experiences. Second, our study reveals the pivotal mediating role of technology trust in translating experiential value into customer satisfaction and behavioral intentions. The strong positive effects of experiential value on technology trust, and subsequently on customer satisfaction and behavioral intentions, highlight the critical importance of building trust in robotic technologies. This finding extends previous research on technology trust in service contexts (Gursoy et al., 2019) by demonstrating its central role in the customer experience-outcome relationship in robotic hospitality settings. Third, our results show that while experiential value significantly influences customer satisfaction, it does not directly affect behavioral intentions. Instead, its impact on behavioral intentions is fully mediated through technology trust and customer satisfaction. This finding underscores the complexity of customer decision-making in robotic hospitality contexts and highlights the need for a holistic approach to understanding and managing customer experiences. Lastly, our multi-group analysis revealed that technology readiness significantly moderates the relationship between service environment innovativeness and experiential value. This suggests that customers with higher technology readiness are more likely to derive greater experiential value from innovative service environments. However, technology readiness did not moderate the other hypothesized relationships, indicating that its influence may be more nuanced than previously thought. In conclusion, this study provides a comprehensive model of customer experiences and behavioral intentions in robotic hospitality settings, offering valuable insights for both academics and practitioners. By illuminating the roles of perceived robot performance, service environment innovativeness, technology trust, and technology readiness, our findings contribute to a more nuanced understanding of customer behavior in increasingly technology-driven hospitality environments. These insights can guide the development of more effective strategies for designing, implementing, and managing robotic services in the hospitality industry, ultimately enhancing customer experiences and driving positive behavioral outcomes.

Theoretical Implications

This study offers several significant theoretical implications that contribute to and extend the existing body of knowledge in hospitality management, service robotics, and technology acceptance. First, our findings contribute to the growing literature on service robots in hospitality by providing a more nuanced understanding of the factors that influence customer experiences. While previous research has emphasized the importance of robot performance (Wirtz et al., 2018) and human-robot interaction (Tussyadiah & Park, 2018), our study reveals that service environment innovativeness plays an equally critical role in shaping experiential value. This extends the theoretical framework for understanding customer experiences in robotic service settings, suggesting that a holistic approach that considers both technological and environmental factors is necessary. Second, our research challenges some existing assumptions about the relative importance of different factors in shaping customer experiences with service robots. The non-significant effects of human-robot interaction quality and perceived sustainability on experiential value contradict some previous findings (e.g., van Doorn et al., 2017; Yu et al., 2021). This suggests that in the context of robotic hospitality, customers may prioritize performance and innovation over interaction quality and sustainability perceptions. This finding calls for a re-evaluation of theoretical models of customer experience in technology-mediated service encounters, particularly in cultural contexts like Korea where technology adoption is high. Third, our study extends the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) by highlighting the crucial mediating role of technology trust in the relationship between experiential value and behavioral outcomes. While previous research has examined trust in technology adoption (Gursoy et al., 2019), our findings suggest that trust plays a more central role than previously thought, fully mediating the impact of experiential value on behavioral intentions. This underscores the need for theoretical models that place greater emphasis on trust-building processes in technology-mediated service contexts. Fourth, our research contributes to the literature on technology readiness by demonstrating its moderating effect on the relationship between service environment innovativeness and experiential value. This finding extends Parasuraman's (2000) technology readiness index (TRI) by showing that its impact may be more specific to certain aspects of the customer experience, rather than having a uniform effect across all dimensions. This suggests a need for more granular theoretical models that account for the varying impacts of individual differences in technology readiness. Fifth, our study provides theoretical insights into the interplay between hedonic and utilitarian aspects of robotic services. The strong influence of both perceived robot performance (a largely utilitarian factor) and service environment innovativeness (a more hedonic factor) on experiential value suggests that customers evaluate robotic services through both functional and experiential lenses. This finding contributes to the ongoing theoretical debate about the relative importance of hedonic and utilitarian factors in technology-mediated services (Venkatesh et al., 2012). Finally, our research extends the theoretical understanding of customer experience formation in high-tech service environments. By demonstrating the complex relationships between various antecedents, experiential value, trust, satisfaction, and behavioral intentions, our study provides a more comprehensive theoretical framework for understanding customer behavior in robotic hospitality settings. This integrated model offers a foundation for future research exploring the psychological mechanisms underlying customer responses to advanced technologies in service contexts.

In conclusion, this study makes significant contributions to theory by extending existing models, challenging some previously held assumptions, and providing new insights into the factors shaping customer experiences and behaviors in robotic hospitality settings. These theoretical implications open up new avenues for research and call for a reconsideration of how we conceptualize and study technology-mediated service experiences in an increasingly automated hospitality industry.

Practical Implications

Our research findings offer several valuable practical implications for hospitality managers, service robot developers, and marketing professionals, particularly in the context of the Korean market and similar technologically advanced environments. The results of our study highlight the critical importance of both robot performance and service environment innovativeness in shaping customer experiences. Hospitality managers should focus on implementing high-performing robots that can efficiently and accurately complete tasks, while simultaneously investing in creating innovative service environments that complement and enhance the robotic service experience. This could involve integrating advanced technologies like augmented reality or interactive displays to create a futuristic and engaging atmosphere that aligns with customers' expectations of high-tech service environments. Given the crucial mediating role of technology trust in our model, businesses must prioritize building and maintaining customer trust in robotic services. This can be achieved through transparent communication about the robots' capabilities and limitations, providing clear instructions on how to interact with the robots, and ensuring robust data privacy and security measures. Managers should also consider implementing a hybrid service model where human staff are available to assist with any issues arising from robot interactions, thereby providing a safety net that can enhance overall trust in the technology. Our findings on the moderating effect of technology readiness suggest that businesses should segment their customers based on their level of technology readiness and tailor their service strategies accordingly. For customers with high technology readiness, emphasizing the innovative aspects of the robotic service environment may be particularly effective. For those with lower technology readiness, a more gradual introduction to robotic services, perhaps with more human support, may be beneficial. This could involve offering customers the choice between robotic and human service, allowing them to become comfortable with the technology at their own pace. The non-significant effect of perceived sustainability on experiential value suggests that current approaches to communicating sustainability in robotic services may not be resonating with customers. However, given the growing importance of sustainability in the hospitality industry, managers should not abandon these efforts. Instead, they should explore more innovative ways to integrate and communicate sustainability initiatives that directly enhance the customer experience. For example, they could gamify sustainability efforts through the robotic interface or use the robots to provide real-time feedback on the environmental impact of customers' choices. While our study found that human-robot interaction quality did not significantly affect experiential value, this doesn't mean it should be neglected. Instead, managers should focus on how robotic services can enhance the overall service experience. This might involve using robots for routine tasks to free up human staff for more complex, high-value interactions. It could also mean designing robot-human collaborations that leverage the strengths of both to create unique and memorable service experiences. Marketing professionals should leverage the insights from this study to develop more effective communication strategies. Emphasizing the performance capabilities of robots, the innovative nature of the service environment, and the measures taken to ensure technology trust could be particularly impactful. Moreover, showcasing how robotic services enhance rather than replace the overall service experience could help address potential concerns from less technologically ready customers. Given the rapid pace of technological change and evolving customer expectations, hospitality businesses should implement systems for continuous monitoring of customer responses to robotic services. Regular surveys, analysis of customer feedback, and ongoing performance metrics can help identify areas for improvement and ensure that robotic services continue to meet and exceed customer expectations. Finally, while our study focused on the Korean market, known for its high technology adoption rates, businesses operating in or expanding to different cultural contexts should be mindful of potential variations in customer perceptions and expectations of robotic services. Adaptation of robotic services to align with local cultural norms and preferences may be necessary for successful implementation in diverse markets. By implementing these practical recommendations, hospitality businesses can more effectively leverage robotic services to enhance customer experiences, build trust, and drive positive behavioral outcomes in an increasingly technology-driven industry. The key lies in balancing technological innovation with human touch, adapting strategies to individual customer needs, and continuously evolving the service offering in response to changing market dynamics and customer expectations.

Limitations and Future Research

While this study provides valuable insights, several limitations offer avenues for future research. Firstly, the study's focus on the Korean context may limit generalizability, necessitating cross-cultural comparisons in future studies. Secondly, the cross-sectional design could be complemented by longitudinal research to examine how perceptions change over time. Thirdly, future studies could employ experimental designs or field studies to observe actual customer behaviors during robot interactions. Additionally, adopting a multi-stakeholder approach, incorporating perspectives from employees and managers, could provide a more holistic understanding. Future research could also explore additional factors such as perceived robot autonomy or the role of customer co-creation in robotic service encounters. Lastly, while our study touched upon sustainability, the non-significant effect warrants further investigation into how customers perceive the sustainability aspects of robotic services. As robotic technologies continue to advance, ongoing research will be crucial to understand their full implications for customer experiences, employee roles, and overall service quality in the hospitality industry.

Appendix A. Survey items

Constructs	Items	Measures	References
Perceived Robot Performance (PRP)	PRP1	The restaurant service robot performs tasks efficiently.	Wirtz et al. (2018)
	PRP2	The restaurant service robot is accurate in its task execution.	
	PRP3	The restaurant service robot is reliable in delivering service.	
	PRP4	The restaurant service robot meets my service expectations.	
Human-Robot Interaction Quality (HRIQ)	HRIQ1	The interaction with the restaurant service robot is natural.	Tussyadiah & Park (2018)
	HRIQ2	The restaurant service robot responds appropriately to my requests.	
	HRIQ3	The communication with the restaurant service robot is clear.	
	HRIQ4	I find it easy to interact with the restaurant service robot.	
Service Environment Innovativeness (SEI)	SEI1	The restaurant's robotic service environment is innovative.	Mathis et al. (2020)
	SEI2	The restaurant offers a unique technological dining experience.	
	SEI3	The robotic service setup in this restaurant is cutting-edge.	
	SEI4	This restaurant's use of robots creates a futuristic atmosphere.	
Perceived Sustainability (PS)	PS1	Using service robots in this restaurant is environmentally friendly.	Yu et al. (2021)
	PS2	The robotic service helps reduce waste in restaurant operations.	
	PS3	The use of service robots contributes to sustainable practices in dining.	
	PS4	This robotic service approach promotes resource efficiency.	
Experiential Value (EV)	EV1	The robotic service experience in this restaurant is enjoyable.	Lu et al. (2019)
	EV2	The robotic service adds value to my dining experience.	
	EV3	I find the robotic service experience in this restaurant memorable.	
	EV4	The robotic service enhances the overall quality of my visit.	
Technology Trust (TT)	TT1	I trust the restaurant service robot to perform reliably.	Gursoy et al. (2019)
	TT2	I believe the restaurant service robot is trustworthy.	
	TT3	I feel confident about the security of interacting with the service robot.	
	TT4	I trust that the service robot will protect my personal information.	

Constructs	Items	Measures	References
Customer Satisfaction (CS)	CS1	I am satisfied with the robotic service provided in this restaurant.	Wirtz et al. (2018)
	CS2	The robotic service meets my expectations.	
	CS3	I have a positive overall impression of the robotic service experience.	
	CS4	I am pleased with my decision to use the robotic service.	
Behavioral Intentions (BI)	BI1	I intend to use this restaurant's robotic service again in the future.	Tussyadiah et al. (2020)
	BI2	I would recommend this restaurant's robotic service to others.	
	BI3	I am willing to pay a premium for this robotic service experience.	
	BI4	I plan to choose this restaurant over others because of its robotic service.	

REFERENCES

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research, 14*(3), 396-402.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science, 16*(1), 74-94.

Belanche, D., Casaló, L. V., & Flavián, C. (2021). Frontline robots in tourism and hospitality: service enhancement or cost reduction? *Electronic Markets, 31*(3), 477-492.

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020). Service robot implementation: a theoretical framework and research agenda. *The Service Industries Journal, 40*(3-4), 203-225.

Byrne, B. M. (2016). *Structural equation modeling with AMOS: Basic concepts, applications, and programming*. 3rd ed. Routledge.

Cha, S. S. (2020). Customers' intention to use robot-serviced restaurants in Korea: Relationship of coolness and MCI factors. *International Journal of Contemporary Hospitality Management, 32*(9), 2947-2968.

Chin, W. W., Thatcher, J. B., & Wright, R. T. (2012). Assessing common method bias: Problems with the ULMC technique. *MIS Quarterly, 36*(3), 1003-1019.

Choi, S., Liu, S. Q., & Mattila, A. S. (2021). "How may I help you?" Says a robot: Examining language styles in the service encounter. *International Journal of Hospitality Management, 92*, 102688.

Choi, Y., Choi, M., Oh, M., & Kim, S. (2021). Service robots in hotels: Understanding the service quality perceptions of human-robot interaction. *Journal of Hospitality Marketing & Management, 30*(5), 617-637.

Choi, Y., Oh, M., Choi, M., & Kim, S. (2021). Exploring the influence of culture on tourist experiences with robots in service delivery. *Current Issues in Tourism, 24*(5), 717-733.

de Kervenoael, R., Hasan, R., Schwob, A., & Goh, E. (2020). Leveraging human-robot interaction in hospitality services: Incorporating the role of perceived value, empathy, and information sharing into visitors' intentions to use social robots. *Tourism Management, 78*, 104042.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

Gössling, S., Hall, C. M., & Weaver, D. B. (2009). *Sustainable tourism futures: Perspectives on systems, restructuring and innovations*. Routledge.

Gursoy, D., & Chi, C. G. (2020). Effects of COVID-19 pandemic on hospitality industry: Review of the current situations and a research agenda. *Journal of Hospitality Marketing & Management, 29*(5), 527-529.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49*, 157-169.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis*. 7th ed. Pearson.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55.

Ivanov, S., Webster, C., & Berezina, K. (2017). Adoption of robots and service automation by tourism and hospitality companies. *Revista Turismo & Desenvolvimento, 27/28*, 1501-1517.

Jung, T., & Cho, M. (2022). Exploring the role of emotionally intelligent AI-powered service robots in enhancing customer experience: Evidence from Korean restaurants. *International Journal of Hospitality Management, 98*, 103088.

Kang, J. W., Choi, Y. J., & Choi, B. S. (2020). AI, Iot, and Blockchain for Sustainable Development Goals. *IEEE Access, 8*, 193930-193937.

Keng, C. J., Huang, T. L., Zheng, L. J., & Hsu, M. K. (2007). Modeling service encounters and customer experiential value in retailing. *International Journal of Service Industry Management, 18*(4), 349-367.

Kim, J. J., & Qu, H. (2014). Customers' perceptions of green practices in restaurants: What do they really care about? *Journal of Tourism and Hospitality Marketing, 31*(8), 930-947.

Kim, J., Kim, M., & Choi, Y. (2023). The impact of COVID-19 on robot adoption in Korean restaurants: A longitudinal study. *International Journal of Hospitality Management, 108*, 103384.

Kim, S. S., Kim, J., Badu-Baiden, F., Giroux, M., & Choi, Y. (2021). Preference for robot service or human service in hotels? Impacts of the COVID-19 pandemic. *International Journal of Hospitality Management, 93*, 102795.

Kim, T. T., & Qu, H. (2014). Employees' perception of customer service robot performance and HR strategies. *International Journal of Contemporary Hospitality Management, 26*(5), 741-765.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. 4th ed. Guilford Publications.

Kuo, C. M., Chen, L. C., & Tseng, C. Y. (2017). Investigating an innovative service with hospitality robots. *International Journal of Contemporary Hospitality Management, 29*(5), 1305-1321.

Kuo, C. M., Chen, L. C., & Tseng, C. Y. (2022). Investigating an innovative service with hospitality robots. *International Journal of Contemporary Hospitality Management, 34*(1), 174-193.

Kwak, M. K., Lee, J., & Cha, S. S. (2021). Senior consumer motivations and perceived value of robot service restaurants in Korea. *Sustainability, 13*(5), 2755.

Lee, S., & Choi, J. (2021). Generational differences in attitudes towards service robots in restaurants: A Korean case study. *Technology in Society, 67*, 101803.

Lee, W. H., Lin, C. W., & Shih, K. H. (2018). A technology acceptance model for the perception of restaurant service robots for trust, interactivity, and output quality. *International Journal of Mobile Communications, 16*(4), 361-376.

Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management, 80*, 36-51.

Lu, L., Zhang, P., & Zhang, T. (2022). How does artificial intelligence affect tourist experiences? The moderating role of technology readiness. *Tourism Management, 89*, 104461.

MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. *Multivariate Behavioral Research, 39*(1), 99-128.

Mathis, E. F., Kim, H. L., Uysal, M., Sirgy, J. M., & Prebensen, N. K. (2016). The effect of co-creation experience on outcome variable. *Annals of Tourism Research, 57*, 62-75.

Ministry of Trade, Industry and Energy. (2020). *Robot Industry Promotion Act*. Government of South Korea.

Moriuchi, E. (2019). Okay, Google!: An empirical study on voice assistants on consumer engagement and loyalty. *Psychology & Marketing, 36*(5), 489-501.

Moussawi, S., Koufaris, M., & Benbunan-Fich, R. (2020). How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents. *Electronic Markets, 31*, 343-364.

Murphy, J., Gretzel, U., & Pesonen, J. (2019). Marketing robot services in hospitality and tourism: The role of anthropomorphism. *Journal of Travel & Tourism Marketing, 36*(7), 784-795.

Nunnally, J. C. (1978). *Psychometric theory*. 2nd ed. McGraw-Hill.

Oliver, R. L. (1997). *Satisfaction: A behavioral perspective on the consumer*. McGraw-Hill.

Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2*(4), 307-320.

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research, 18*(1), 59-74.

Park, S. (2020). Multifaceted trust in tourism service robots. *Annals of Tourism Research, 81*, 102888.

Park, S., & Kwon, J. (2020). The impact of demographic challenges on service robot adoption in the Korean hospitality industry. *Service Business, 14*, 419-442.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879-891.

Rosenbaum, M. S., & Wong, I. A. (2015). If you install it, will they use it? Understanding why hospitality customers take "technological pauses" from self-service technology. *Journal of Business Research, 68*(9), 1862-1868.

Schumacker, R. E., & Lomax, R. G. (2016). *A beginner's guide to structural equation modeling*. 4th ed. Routledge.

Shin, H., & Perdue, R. R. (2022). Self-service technology in the hospitality industry: The influence of technology readiness on customer satisfaction and behavioral intentions. *International Journal of Hospitality Management, 94*, 102877.

Steenkamp, J. B. E., & Baumgartner, H. (1998). Assessing measurement invariance in cross-national consumer research. *Journal of Consumer Research, 25*(1), 78-90.

Tuomi, A., Tussyadiah, I. P., & Stienmetz, J. (2020). Applications and implications of service robots in hospitality. *Cornell Hospitality Quarterly, 61*(3), 299-311.

Tuomi, A., Tussyadiah, I. P., & Stienmetz, J. (2021). Service robots and the changing roles of employees in restaurants: A cross cultural study. *International Journal of Contemporary Hospitality Management, 33*(11), 3774-3796.

Tung, V. W. S., & Au, N. (2018). Exploring customer experiences with robotics in hospitality. *International Journal of Contemporary Hospitality Management, 30*(7), 2680-2697.

Tussyadiah, I. (2020). A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism. *Annals of Tourism Research, 81*, 102883.

Tussyadiah, I. P., & Park, S. (2018). Consumer evaluation of hotel service robots. In B. Stangl & J. Pesonen (Eds.), *Information and Communication Technologies in Tourism 2018* (pp. 308-320). Springer.

Tussyadiah, I. P., Zach, F. J., & Wang, J. (2020). Do travelers trust intelligent service robots? *Annals of Tourism Research, 81*, 102886.

van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers' service experiences. *Journal of Service Research, 20*(1), 43-58.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178.

Verma, R., Stock, D., & McCarthy, L. (2019). Customer experiences with hotel technologies: A comparison of millennials and older travelers. *International Journal of Hospitality Management, 76*, 102-110.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management, 29*(5), 907-931.

Yu, Y., Li, X., & Jai, T. M. (2021). The impact of green experience on customer satisfaction: Evidence from TripAdvisor. *International Journal of Contemporary Hospitality Management, 29*(5), 1340-1361.

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of Marketing, 60*(2), 31-46.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.