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Enhancing Human-Robot Interaction in Chinese Hospitality: Empathy, Anthropomorphism, Competence on Service Robot Actual Usage

Yan Zhou[1,2]

[1]UCSI Graduate Business School, UCSI University, Kuala Lumpur, Malaysia
[2]Chongqing College of Finance and Economics, Chongqing City 402160, China
E-mail ID: 1002163344@ucsiuniversity.edu.my

This study explores how perceived usefulness, empathy, and information dissemination collectively influence users' attitudes and actual usage intentions of service robots in hospitality contexts. Drawing on the Technology Acceptance Model (TAM) and the Artificially Intelligent Device Use Acceptance (AIDUA) framework, we integrate functional (perceived usefulness, information dissemination) and emotional (empathy) factors to construct a more comprehensive theoretical model. We further examine anthropomorphism and technological competence as moderators, elucidating how human-like qualities and reliable performance can strengthen the effect of functional attributes on attitude formation. Using a quantitative approach, our empirical findings confirm that perceived usefulness, empathy, and information dissemination jointly foster positive attitudes, which in turn increase actual usage intentions. Moderation analyses reveal that anthropomorphism magnifies the impact of perceived usefulness on attitudes, while technological competence enhances the influence of information dissemination on attitudes. Attitude formation also mediates the relationships between these antecedents and usage intentions, demonstrating that users' initial impressions evolve into enduring behavioral commitments. This study integrates functional and emotional dimensions into existing frameworks, seeing perceived usefulness, empathy, and information dissemination as interconnected. Anthropomorphism and technological competence serve as moderators, enhancing operational efficiency and emotional engagement. The results offer both scholarly and practical insights, guiding creation of empathetic, trustworthy service robots that transcend conventional adoption models. Ultimately, the research fosters immersive, trust-enhancing hospitality experiences, cultivating deeper, more enduring guest relationships for sustainable

competitive advantage.

Keywords: Human-Robot Interaction; Service Robots; Perceived Usefulness; Anthropomorphism; Information Dissemination

1. Introduction

1.1 Background

The integration of robotics into the hospitality industry marks a transformative shift, redefining operational efficiencies and enhancing guest experiences through advancements in artificial intelligence (AI) and automation (Ivanov & Webster, 2019). Service robots have emerged as key drivers of innovation, addressing challenges such as labor shortages and the demand for more personalized services (Li et al., 2019; Murphy et al., 2017). These technologies do not merely optimize workflows; they also open new research avenues in hospitality management. Robots with anthropomorphic designs can mimic human traits to foster rapport and enhance service acceptability (Choi & Huang, 2021; Tussyadiah, 2020). Their human-like qualities—such as empathy—align with evolving demands for more engaging and intuitive customer experiences. Service robots not only enhance operational efficiency but also hold significant potential in enriching customer experiences (Doborjeh et al., 2022). Furthermore, the perceived benefits of customer loyalty programs are closely linked to customer happiness and satisfaction, emphasizing the need for a balanced approach in service robot design that addresses both functional and emotional aspects (Agarwal et al., 2022).

Service robots now undertake diverse roles, including concierge tasks, room deliveries, and information dissemination. Their 24/7 availability was particularly valuable during the COVID-19 pandemic, as robots minimized human contact, reinforced hygiene standards, and bolstered customer trust (Shin et al., 2019). Additionally, their capacity to handle multilingual interactions and offer tailored recommendations highlights their potential to address the increasingly heterogeneous needs of guests (Kuo et al., 2017). However, these technological advancements raise concerns about displacing human workers and possibly eroding the personalized, human-centered essence of hospitality. To manage these ethical dilemmas, research emphasizes human-robot collaboration, merging human empathy with robotic consistency to provide operational benefits without neglecting the emotional dimension of service (Lu et al., 2019). Emerging studies on empathy-driven AI and Internet of Things (IoT) integrations underscore the significance of robots as both functional tools and emotional enablers in modern hospitality environments (Wang & Xiang, 2012; Santos et al., 2017).

1.2 Theoretical Foundations

This study draws upon the Technology Acceptance Model (TAM) and the Artificially Intelligent Device Use Acceptance (AIDUA) framework. TAM focuses on the functional aspects of technology acceptance—particularly perceived usefulness and perceived ease of use (Davis, 1989; Venkatesh et al., 2003). Within hospitality, previous research demonstrates that perceived usefulness contributes to how guests evaluate service robots' capacity to improve efficiencies, while perceived ease of use minimizes barriers to adoption. However, TAM underplays the emotional dimensions of service, which are vital in contexts emphasizing warmth and personal interaction.

To address this limitation, the AIDUA framework complements TAM by incorporating hedonic motivations, trust, and perceived risk—factors that reflect the relational and experiential character of hospitality services (Belanche et al., 2019). Trust mitigates concerns around reliability and privacy, while hedonic benefits encourage customers to perceive robots as not only functional but also enjoyable and engaging (Shin, 2013). Integrating empathy into this conceptualization acknowledges that guests not only value operational efficiency but also seek emotionally resonant service encounters. Moreover, non-linear models indicate that user acceptance of robo-advisory services is influenced by intricate emotional and cognitive factors beyond mere perceived usefulness (Aw et al., 2023). Additionally, the impact of green self-identity on behavioral intentions suggests that incorporating sustainable features in service robots can enhance positive user attitudes (Becerra et al., 2023).

1.3 Research Gaps

Despite the advances in applying robotic technologies to hospitality, key gaps persist. Many studies isolate perceived usefulness, empathy, and information dissemination rather than examining their combined influence on attitude formation and actual usage intentions (Ayyildiz et al., 2022; Castelo et al., 2023). Moreover, the increasing deployment of service robots raises concerns regarding privacy and intrusion, which have not been adequately addressed in existing research (Aw et al., 2024). Similarly, while information dissemination can enhance trust and transparency, its interplay with other factors in shaping positive attitudes and sustained usage intentions is not well understood (Wang & Xiang, 2012).

In addition, most research focuses on initial impressions rather than the longer-term attitudinal shifts resulting from repeated guest-robot interactions. Understanding how attitudes evolve over time is critical for designing service robots that foster enduring guest loyalty (Shin et al., 2019). Moreover, the moderating roles of anthropomorphism and technological competence remain insufficiently explored. Anthropomorphic features may amplify the emotional resonance of functional attributes, and technological competence can ensure reliability and adaptability, both potentially shaping how customers balance functional and emotional expectations over extended periods (Choi & Huang, 2021).

1.4 Research Questions

To address these gaps, this study proposes the following research questions:

- How do Perceived Usefulness, Empathy, and Information Dissemination jointly influence Attitude Formation and Actual Usage Intentions in hospitality contexts?
- How do Anthropomorphism and Technological Competence moderate the relationships between (a) Perceived Usefulness and Attitude Formation, and (b) Information Dissemination and Attitude Formation?
- How does Attitude Formation mediate the relationships between Perceived Usefulness, Empathy, Information Dissemination, and Actual Usage Intentions?

These questions aim to illuminate both functional and emotional facets of service robot adoption in hospitality (Murphy et al., 2019).

1.5 Research Contribution

This research contributes to the literature by integrating functional (perceived usefulness, information dissemination) and emotional (empathy) dimensions within a comprehensive theoretical framework, thereby offering a more holistic explanation of service robot adoption in hospitality (Tussyadiah, 2020). By examining how these dimensions collectively shape attitudes and actual usage intentions, we move beyond models that consider only operational efficiency or emotional engagement independently (Ivanov & Webster, 2019).

Furthermore, introducing anthropomorphism and technological competence as moderators enriches the analysis. Anthropomorphism can strengthen the link between functional value and attitudinal outcomes, while technological competence ensures that communicated functionalities translate into dependable performance (Choi & Huang, 2021). By explicating these moderating effects, we provide insights into how both design elements and technical reliability influence guests' evolving perceptions (Kuo et al., 2017).

Finally, this study highlights the mediating role of attitude formation, illuminating how guests' initial perceptions evolve into stable intentions over repeated interactions (Yoo et al., 2017). Emphasizing empathy's role in building positive attitudes and trust, this research underscores that successful robotic service design requires blending functional excellence with emotional resonance (Lu et al., 2019). These insights are invaluable for hospitality organizations seeking to implement service robots that foster deep, lasting guest relationships.

2. Theoretical Underpinnings and Literature Review

2.1 Technology Acceptance Model (TAM): A Functional Foundation

TAM has long been a cornerstone for understanding technology acceptance. In hospitality, TAM's core constructs—PU and PEOU—explain how customers evaluate robots as tools that streamline check-ins, handle routine inquiries, or offer personalized recommendations (Agarwal & Prasad, 1998; Ajzen, 1991). While TAM successfully captures the functional aspects of adoption, it underplays the emotional elements inherent in service interactions (Mukherjee et al., 2023; Chan & Tung, 2019). To address this limitation, the current study integrates empathy, acknowledging that emotional engagement can significantly shape how customers perceive and interact with service technologies.

2.2 Artificially Intelligent Device Use Acceptance (AIDUA): Bridging Emotional Dynamics

The AIDUA framework complements TAM by highlighting hedonic motivations, trust, and perceived risk (Chi et al., 2021). These factors become especially important in hospitality, where service experiences are not solely transactional but also relational and experiential. Anthropomorphic elements, such as human-like speech or facial expressions, increase robots' emotional resonance and trustworthiness. Simultaneously, technological competence underpins consistent and adaptive performance, which is crucial for earning customer trust.

2.3 Perceived Usefulness (PU), Empathy (EM), Information Dissemination (ID), Attitude Formation (AF), and Actual Usage Intentions in Hospitality (AUI)

2.3.1 Perceived Usefulness (PU) and Actual Usage Intentions (AUI)

Perceived Usefulness (PU) describes a user's belief that a technology enhances performance, efficiency, and convenience. Trust and cultural factors are pivotal in determining customers' acceptance of artificially intelligent service robots, further influencing perceived usefulness (Chi et al., 2023). Similarly, the integration of technology with fashion and psychographic attributes can sustain the usage of smart devices, highlighting the multifaceted nature of perceived usefulness (Kamal Basha et al., 2022). In hospitality contexts, service robots can streamline check-ins, expedite requests, and facilitate personalized recommendations, ultimately reducing guests' waiting times and operational inefficiencies. Such tangible improvements instill confidence and highlight the functional value of the robot, encouraging guests to view it as a reliable support tool (McLean & Osei-Frimpong, 2019). As perceptions of usefulness rise, guests are more inclined to integrate the robot into their service experiences, thereby shaping stronger Actual Usage Intentions (AUI). Studies have shown that when technologies address user needs effectively, adoption likelihood increases. In the hospitality domain, which emphasizes comfort, convenience, and service quality, the positive relationship between PU and AUI becomes particularly salient. By enhancing overall task performance, PU bridges the gap between initial curiosity and sustained engagement, converting functional appreciation into behavioral commitments. Consequently, service robots that consistently demonstrate their utility can expect higher patronage and more frequent usage, as customers incorporate these technologies seamlessly into their hospitality journey.
H1: Perceived Usefulness is positively related to Actual Usage Intentions in Hospitality.

2.3.2 Information Dissemination (ID) and Actual Usage Intentions (AUI)
Information Dissemination (ID) involves the clear, accurate, and relevant communication of a service robot's capabilities, features, and procedures. Within hospitality, guests often seek assurance through transparent and accessible information to reduce uncertainty. By proactively explaining its functions—such as multilingual support, hygiene standards, or real-time responsiveness—the robot fosters trust and lowers perceived risk (Wirtz et al., 2018). This clarity enables guests to align their expectations with the robot's actual offerings, minimizing cognitive dissonance and skepticism. Empirical evidence shows that well-informed customers are more likely to embrace technology, as they understand its value proposition and feel confident in using it. Thus, effective ID encourages customers to move beyond passive observation toward active engagement, reinforcing their Actual Usage Intentions (AUI). Over time, consistent and strategic information delivery builds credibility, ensuring that guests rely on the robot's guidance and functionalities. The result is a smoother user experience, greater perceived value, and ultimately, a higher likelihood of integrating the robot into recurring service encounters. In an industry where trust and reassurance are paramount, ID emerges as a fundamental driver of technology adoption intentions.
H2: Information Dissemination is positively related to Actual Usage Intentions in Hospitality.

2.3.3 Perceived Usefulness (PU) and Attitude Formation (H3)
Attitude Formation (AF) involves users' cognitive and affective evaluations that shape their overall predisposition toward a technology. In hospitality, Perceived Usefulness (PU) serves as a critical antecedent to forming positive attitudes toward service robots. When a robot demonstrably enhances service quality—improving efficiency, accuracy, and convenience—guests are likely to develop a favorable mental framework toward its use (Huang & Rust, 2021). PU not only addresses functional needs but also reduces uncertainty and perceived risk,

encouraging users to view the robot as trustworthy and dependable. As these positive impressions accumulate, they transform into stable, positive attitudes that endure over multiple encounters. This attitudinal shift is rooted in the user's recognition of tangible benefits, ensuring that the robot is seen not as a novelty but as a valuable asset. By consistently delivering on functional promises, the robot reinforces its perceived efficacy. As a result, favorable attitudes form, persist, and influence subsequent decisions, laying a solid foundation for long-term acceptance and adoption behavior.
H3: Perceived Usefulness is positively related to Attitude Formation.

2.3.4 Empathy (EM) and Attitude Formation (H4)
Empathy (EM) reflects a service robot's ability to understand and respond appropriately to customers' emotions, needs, and concerns. In the hospitality industry—where interpersonal warmth, personalized attention, and emotional resonance are essential—robots that demonstrate empathic cues significantly shape Attitude Formation (AF) (Song et al., 2023). Empathetic creativity among frontline employees is crucial for fostering emotional connections with customers in the age of service robots (Do et al., 2023). This emphasizes the importance of integrating empathic interactions in service robot design to enhance user attitudes.By adjusting language, tone, or even gestures to reflect guests' emotional states, the robot reduces anxiety, instills comfort, and fosters a sense of human-like care. Such empathetic engagement encourages guests to perceive the robot as more than a mechanical tool; it becomes a supportive companion that understands their preferences and dilemmas. Over time, these positive emotional interactions transform into stable attitudes as trust and relational value accumulate . Guests who feel emotionally acknowledged by the robot are more inclined to develop favorable attitudes, ultimately influencing their propensity to accept and utilize the technology. Therefore, empathy serves as a powerful catalyst in bridging functional capabilities with emotional connectivity, resulting in more meaningful and enduring attitudinal shifts in the hospitality service landscape.
H4: Empathy is positively related to Attitude Formation.

2.3.5 Information Dissemination (ID) and Attitude Formation (H5)
Information Dissemination (ID) not only influences usage intentions but also profoundly affects Attitude Formation (AF). Effective communication strategies significantly influence consumer reactions to service bots, enhancing user trust and satisfaction (Castelo et al., 2023). Additionally, leveraging the Computers Are Social Actors (CASA) paradigm, service robots in retail environments drive repeat purchase intentions through strategic information dissemination (de Kervenoael et al., 2024).When a service robot communicates its functionalities, features, and processes clearly, guests gain a transparent understanding of what to expect (Hwang et al., 2020). This clarity reduces uncertainty, enhances perceived reliability, and instills a sense of control. As confusion and mistrust diminish, positive attitudes emerge, supported by the belief that the robot is both competent and forthcoming (Gelbrich et al., 2021). Furthermore, effective ID aligns user expectations with the robot's actual performance, reinforcing consistency and predictability. Over time, guests who feel well-informed tend to view the robot more favorably, perceiving it as a knowledgeable and responsive service partner. Studies indicate that when communication is tailored, context-specific, and accessible, it enriches user experiences, ultimately fostering more positive and stable attitudes. In essence, ID catalyzes the cognitive process that underpins AF: it builds a bridge between functional

understanding and emotional reassurance, establishing a foundation of trust and confidence that shapes how guests evaluate the robot's role in the hospitality ecosystem. H5: Information Dissemination is positively related to Attitude Formation.

2.4 Moderating Effects of Anthropomorphism (AN) and Technological Competence (TC)

2.4.1 Anthropomorphism (AN) as a Moderator for PU→AF (H6) Anthropomorphism (AN) involves imbuing service robots with human-like attributes—such as facial expressions, gestures, and a conversational tone—to evoke a sense of familiarity and emotional resonance. Speciesism moderates the effect of robot intelligence on customer perceptions and behavior, indicating that anthropomorphic design must consider potential biases related to users' perceptions of different robot 'species' (Fiestas Lopez Guido et al., 2024). Furthermore, the human-likeness of robots significantly impacts customer responses, with higher degrees of anthropomorphism leading to enhanced emotional engagement and satisfaction (Grazzini et al., 2023).While Perceived Usefulness (PU) lays the groundwork for positive attitudes by highlighting functional value, anthropomorphic features elevate these attitudes by adding an affective dimension. When users see a robot as not only useful but also engaging, personable, and approachable, their cognitive appreciation merges with emotional affinity. This synergy magnifies the positive effect of PU on Attitude Formation (AF) (Tung & Au, 2018). Guests are more likely to embrace a highly useful robot if it feels relatable, transforming utilitarian benefits into a more holistic, gratifying experience. In other words, AN intensifies the link between functional appraisal and emotional attachment, making the resulting attitudes more deeply embedded and enduring. By fostering relatable interactions, AN encourages guests to interpret the robot's usefulness through a humanized lens, ultimately enhancing the magnitude and stability of their positive attitudinal responses. H6: Anthropomorphism positively moderates the relationship between Perceived Usefulness and Attitude Formation.

2.4.2 Technological Competence (TC) as a Moderator for ID→AF (H7) Technological Competence (TC) reflects the service robot's ability to operate accurately, reliably, and adaptively, ensuring that its communicated functionalities are consistently executed. While Information Dissemination (ID) establishes expectations by informing users about the robot's capabilities, TC validates these claims, thereby strengthening the link between ID and Attitude Formation (AF) (Lin & Chang, 2011). When guests witness that the robot's actual performance aligns with the conveyed information, their trust and confidence intensify. The robot's demonstrated competence assures users that the promises made through information sharing are not empty but actionable and dependable. This confirmation process transforms cognitive acceptance into stable positive attitudes. Without sufficient TC, even the most transparent communication may fail to inspire strong positive evaluations, as users remain skeptical about the robot's real abilities. Hence, TC acts as a quality filter that ensures ID's messages translate into tangible, reliable service outcomes, ultimately producing more robust and enduring positive attitudes within the hospitality context. H7: Technological Competence positively moderates the relationship between Information Dissemination and Attitude Formation.

2.5 Attitude Formation (AF) as a Mediator

Attitude Formation (AF) as a Mediator (H8)

Attitude Formation (AF) functions as a psychological conduit that integrates functional and emotional inputs—Perceived Usefulness (PU), Empathy (EM), and Information Dissemination (ID)—into cohesive evaluative stances that directly shape Actual Usage Intentions (AUI). In hospitality, a positive attitude crystallizes when guests perceive the robot as simultaneously beneficial, empathetic, and transparent (Rezvani et al., 2017). Once such attitudes solidify, they guide decision-making processes, leading guests from initial curiosity to deliberate adoption and sustained usage (Christou & Chatzigeorgiou, 2020). Empirical evidence suggests that when attitudes are favorable, guests are more inclined to trust the technology, anticipate satisfying experiences, and show greater loyalty. Over time, these stable attitudes become a reliable predictor of how frequently and extensively guests engage with service robots. By acknowledging AF's mediating role, hospitality practitioners can pinpoint where to intervene—enhancing perceived usefulness, delivering empathic interactions, and ensuring effective information dissemination—to optimize long-term adoption and integration. Ultimately, AF translates multifaceted perceptions into intention-driven behavior, illuminating the path from conceptual appreciation to concrete hospitality technology usage. H8: Attitude Formation is positively related to Actual Usage Intentions in Hospitality.

The proposed model. The model proposed for this research is shown in Fig. 1.

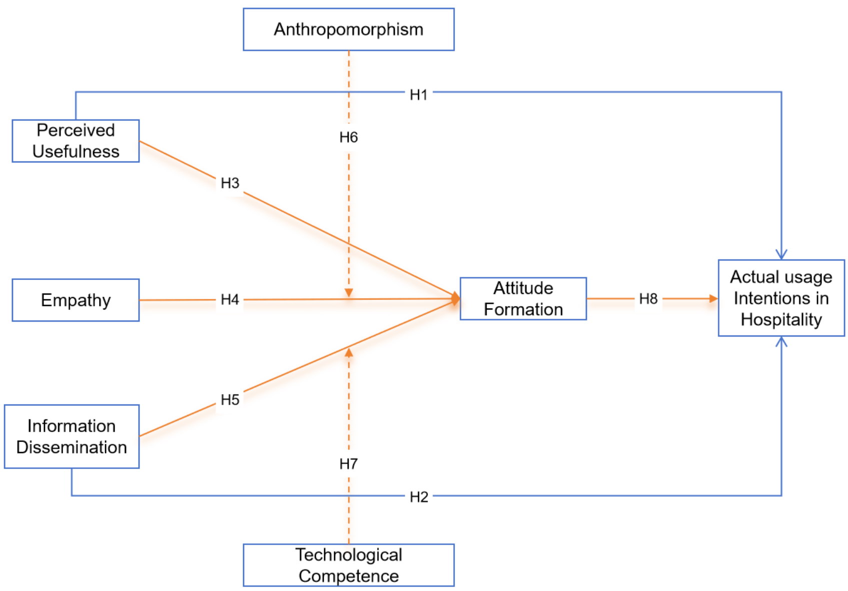

Fig. 1 Proposed research model

3. Research Methodology

3.1 Research Philosophy

This study adopts a positivist research paradigm, emphasizing objective observation, empirical evidence, and hypothesis testing to derive generalizable conclusions (Bryman & Bell, 2015;

Creswell, 2014). Positivism is particularly suited to quantitative investigations in the hospitality and tourism industry, where replicable and reliable methods can systematically capture user attitudes toward service robots (Neuman, 2014). By focusing on structured research designs and statistical rigor, this paradigm facilitates an examination of both functional and emotional dimensions of technology acceptance (Podsakoff et al., 2012).

Drawing on this philosophical stance, the study follows a deductive approach, leveraging theoretical models such as the Technology Acceptance Model (TAM) and the Artificially Intelligent Device Use Acceptance (AIDUA) framework to formulate research hypotheses (Taherdoost, 2019). Constructs such as empathy and information dissemination are incorporated to capture the nuanced interplay between functional and emotional factors in hospitality. This integrated approach ensures alignment between theory and practice, offering deeper insights into real-world adoption challenges of service robots (Chang & Hsu, 2022).3.2 Research Population and Sampling

3.2.1 Population

The target population comprises hospitality and tourism customers who have engaged with service robots across multiple touchpoints, such as hotel check-in counters, concierge services, restaurant ordering and delivery, and airport assistance. Table 1 provides a comprehensive demographic overview of the 210 valid respondents, all of whom indicated Chinese nationality. The age distribution skews toward younger cohorts, with 29.52% between 26 and 35 years old, 19.52% between 18 and 25, 20.00% between 36 and 45, 17.62% under 18, 9.52% between 46 and 55, and 3.81% aged 56 or above. Gender distribution shows 52.86% identified as female, 47.14% as male. In terms of educational attainment, 44.29% hold a bachelor's degree, 21.43% an associate's degree, 20.00% high school or below, 11.43% a master's degree, and 2.86% a doctorate or above. The most common professions include service industry workers (27.14%), technical or engineering professionals (23.33%), managers (20.00%), and students (18.10%). Monthly income levels vary, with 37.62% earning ¥3,001 to ¥5,000, 27.14% earning ¥5,000 to ¥10,000, 12.86% above ¥10,000, 11.90% below ¥3,000, and 10.48% preferring not to disclose income. Regarding service robot usage, 66.19% reported prior experience, whereas 33.81% had never interacted with such technology. Among users, 19.05% rarely use service robots, 23.81% do so occasionally, 15.71% engage monthly, and 10.00% interact weekly or more often. These characteristics illustrate a broad cross-section of the population, thereby providing a robust foundation for investigating service robot adoption and its potential implications in China's hospitality sector (Chen et al., 2022).

Table 1: Descriptive statistics (n=210).

Demographics/Characteristics	Specifications	Counts	Counts Proportion (in %)
Age	Under 18	37	17.62
	18-25	41	19.52
	26-35	62	29.52
	36-45	42	20.00
	46-55	20	9.52
	56 or above	8	3.81
Gender	Female	111	52.86

	Male	99	47.14
	Associate's degree	45	21.43
	Doctorate or above	6	2.86
Educational level	Bachelor's degree	93	44.29
	Master's degree	24	11.43
	High school or below	42	20.00
Country/Nationality	Chinese	210	100.00
	Other	24	11.43
	Student	38	18.10
Current profession	Service industry worker	57	27.14
	Technical/engineering professional	49	23.33
	Manager	42	20.00
	Lower than ¥3,000	25	11.90
	¥3,001-5,000	79	37.62
Monthly income	¥5,000-10,000	57	27.14
	Above ¥10,000	27	12.86
	Prefer not to disclose	22	10.48
Experience of service robot use	No	71	33.81
	Yes	139	66.19
	Never	66	31.43
	Rarely (1-3 times)	40	19.05
Frequency of service robot use	Occasionally (4-10 times)	50	23.81
	Frequently (11-19 times)	33	15.71
	Very frequently (above 20 times)	21	10.00

3.2.2 Sampling Technique

A non-probability purposive sampling method was employed to ensure that all respondents had direct experience with service robots. A total of 234 questionnaires were collected; after excluding incomplete entries, 210 valid responses were retained. This approach enhances the representativeness of the sample in terms of exposure to robotic services (Quinlan et al., 2019). By covering diverse demographics—including varying age groups, education levels, and usage experiences—the sample offers robust insights into user attitudes toward service robots in hospitality.

3.2.3 Ethical Considerations

The study adhered to the ethical principles outlined in the Declaration of Helsinki. All participants provided informed consent, participation was voluntary, and anonymity was strictly maintained. The questionnaire was designed to minimize respondent fatigue and required approximately 15 minutes to complete (Zikmund et al., 2013).

3.3 Research Instrument and Statistical Techniques

3.3.1 Questionnaire Design

The survey instrument was developed based on the Technology Acceptance Model (TAM) and the Artificially Intelligent Device Use Acceptance (AIDUA) framework. All items were measured using five-point Likert scales (1 = Strongly Disagree, 5 = Strongly Agree), focusing on core constructs such as Perceived Usefulness (PU), Empathy (EM), and Information Dissemination (ID). Additional variables included Attitude Formation (AF), Anthropomorphism (AN), and Technological Competence (TC), drawing on established scales from previous studies (Harrington et al., 2017; Kim & Qu, 2014). Expert reviews and a pilot test confirmed initial validity and reliability, with Cronbach's alpha coefficients exceeding 0.7 (Cronbach, 1951).

Nonetheless, certain constructs—specifically Technological Competence (TC) and Attitude Formation (AF)—exhibited relatively low Average Variance Extracted (AVE) and Composite Reliability (CR) in the final dataset, suggesting potential limitations in item design or clarity. To address these issues, we plan to (1) re-examine item wording and reduce redundancy or ambiguity; (2) incorporate newly refined or alternative scales in subsequent studies, followed by multiple rounds of pilot testing to enhance internal consistency and discriminant validity; and (3) integrate qualitative feedback (e.g., interviews, focus groups) to better capture users' perceptions of TC and AF, thereby improving measurement precision and interpretability for both researchers and practitioners (Bagozzi & Yi, 2012).

3.3.2 Translation and Validation

To ensure linguistic and cultural equivalence, Brislin's (1970) back-translation technique was applied to convert the original English questionnaire into Chinese, followed by cross-verification. In future studies involving multiple cultural contexts or international samples, we intend to adapt and validate these scales to maintain cultural appropriateness, which may help address nuances in technology adoption across different regions (Douglas & Craig, 2007).

3.3.3 Data Analysis Techniques

Data analysis was performed using SPSS 26.0 and AMOS 24.0, focusing on reliability, validity, and hypothesis testing through structural equation modeling (SEM). Internal consistency was assessed using Cronbach's alpha and Composite Reliability (CR). Exploratory and Confirmatory Factor Analyses (EFA and CFA) confirmed the constructs' validity based on thresholds for AVE (> 0.5) and KMO (> 0.7) (Fornell & Larcker, 1981).

Subsequently, SEM was applied to evaluate the hypothesized relationships, with model fit indices such as CFI (> 0.9) and RMSEA (< 0.08) confirming the suitability of the model. Multi-group SEM was employed to examine the moderating effects of anthropomorphism and technological competence, while mediation effects of attitude formation were tested via bootstrapping with 5,000 resamples (Byrne, 2016).

Moreover, the χ^2 test result from Table 2 ($\chi^2 = 1.165$, $p = 0.979$) indicates an excellent model fit, confirming the reliability of the multiple-choice data measurement (Tabachnick & Fidell, 2013). Collectively, these findings highlight the functional versatility and growing acceptance of service robots in restaurant services, airport or transportation facilities, cleaning, and retail contexts. Notably, restaurant service robots exhibit the highest usage rate (14.99%) and response rate (59.52%), followed closely by airport and transportation service robots (14.87% usage, 59.05% response). Meanwhile, hotel check-in/check-out robots (13.55% usage, 53.81% response) show moderate but steady development, suggesting opportunities for further refinement in design and user experience (Dickinger & Stangl, 2013).

Table 2: Multiple Choice Frequency Distribution

Items	Response		Prevalence Rate （n=210）
	n	Response Rate	
Hotel check-in/check-out robots	113	13.55%	53.81%
Restaurant service robots (e.g., food delivery, order taking)	125	14.99%	59.52%
Concierge or information robots	114	13.67%	54.29%
Cleaning robots	116	13.91%	55.24%
Airport or transportation service robots	124	14.87%	59.05%
Retail or shopping assistant robots	121	14.51%	57.62%
Other	121	14.51%	57.62%
Total	834	100%	397.14%

Note: Model Fit Test: $\chi2$ = 1.165 p = 0.979

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between 18 and 25, and 20.00% between 36 and 45, while 17.62% are under 18 and 3.81% are 56 or above. Gender is almost evenly split, as 48.10% identified as female and another 48.10% as male; notably, 2.38% reported a non-binary or other gender, and 1.43% preferred not to disclose. In terms of educational attainment, 44.29% hold a bachelor's degree, followed by 21.43% with an associate's degree, 20.00% with high school or below, 11.43% with a master's degree, and 3.81% holding a doctorate or above. The most common professions include service industry workers (27.14%), technical or engineering professionals (23.33%), managers (20.00%), and students (18.10%). Annual income levels vary, with 37.62% earning between ¥100,000 and ¥200,000, 27.14% earning ¥50,000 to ¥100,000, 12.86% above ¥200,000, and 11.90% below ¥50,000; 10.48% preferred not to disclose income. Regarding service robot usage, 66.19% reported prior experience, whereas 31.43% had never interacted with such technology. Among users, 19.05% rarely use service robots, 23.81% do so occasionally, 15.71% engage monthly, and 10.00% interact weekly or more often. These characteristics illustrate a broad cross-section of the population, providing a robust foundation for investigating service robot adoption and its potential implications in China's hospitality sector.

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3.3.1 Questionnaire Design

The survey instrument was developed based on the Technology Acceptance Model (TAM) and the Artificially Intelligent Device Use Acceptance (AIDUA) framework. All items were measured using five-point Likert scales (1 = Strongly Disagree, 5 = Strongly Agree), focusing on core constructs such as Perceived Usefulness (PU), Empathy (EM), and Information Dissemination (ID). Additional variables included Attitude Formation (AF), Anthropomorphism (AN), and Technological Competence (TC), drawing on established scales from previous studies (Harrington et al., 2017; Kim & Qu, 2014). Expert reviews and a pilot test confirmed initial validity and reliability, with Cronbach's alpha coefficients exceeding 0.7 (Cronbach, 1951).

Nonetheless, certain constructs—specifically Technological Competence (TC) and Attitude Formation (AF)—exhibited relatively low Average Variance Extracted (AVE) and Composite

Reliability (CR) in the final dataset, suggesting potential limitations in item design or clarity (Hair et al., 2019). To address these issues, we plan to (1) re-examine item wording and reduce redundancy or ambiguity; (2) incorporate newly refined or alternative scales in subsequent studies, followed by multiple rounds of pilot testing to enhance internal consistency and discriminant validity; and (3) integrate qualitative feedback (e.g., interviews, focus groups) to better capture users' perceptions of TC and AF, thereby improving measurement precision and interpretability for both researchers and practitioners (Bagozzi & Yi, 2012).

3.3.2 Translation and Validation

To ensure linguistic and cultural equivalence, Brislin's (1970) back-translation technique was applied to convert the original English questionnaire into Chinese, followed by cross-verification. In future studies involving multiple cultural contexts or international samples, scales should be adapted and validated to maintain cultural appropriateness, which may help address nuances in technology adoption across different regions (Douglas & Craig, 2007).

3.3.3 Data Analysis Techniques

Data analysis was performed using SPSS 26.0 and AMOS 24.0, focusing on reliability, validity, and hypothesis testing through structural equation modeling (SEM). Internal consistency was assessed using Cronbach's alpha and Composite Reliability (CR). Exploratory and Confirmatory Factor Analyses (EFA and CFA) confirmed the constructs' validity based on thresholds for AVE (> 0.5) and KMO (> 0.7) (Fornell & Larcker, 1981).

Subsequently, SEM was applied to evaluate the hypothesized relationships, with model fit indices such as CFI (> 0.9) and RMSEA (< 0.08) confirming the suitability of the model (Kline, 2016). Multi-group SEM was employed to examine the moderating effects of anthropomorphism and technological competence, while mediation effects of attitude formation were tested via bootstrapping with 5,000 resamples (Byrne, 2016).

Moreover, the χ^2 test result from Table 2 ($\chi^2 = 1.165$, $p = 0.979$) indicates an excellent model fit, confirming the reliability of the multiple-choice data measurement (Tabachnick et al., 2014). Collectively, these findings highlight the functional versatility and growing acceptance of service robots in restaurant services, airport or transportation facilities, cleaning, and retail contexts. Notably, restaurant service robots exhibit the highest usage rate (14.99%) and response rate (59.52%), followed closely by airport and transportation service robots (14.87% usage, 59.05% response). Meanwhile, hotel check-in/check-out robots (13.55% usage, 53.81% response) show moderate but steady development, suggesting opportunities for further refinement in design and user experience (Dickinger & Stangl, 2013).

4. Data Analysis

4.1 Reliability and Validity

As shown in Table 3, reliability and validity assessments reveal varying degrees of construct robustness across constructs. Anthropomorphism (AN) demonstrates strong internal consistency, with Composite Reliability (CR) = 0.866 and Cronbach's alpha = 0.863—both exceeding 0.7 (DeVellis, 2017). Information Dissemination (ID) and Empathy (EM) also meet recommended thresholds (CR > 0.7), specifically 0.764 and 0.749, respectively. By contrast, Technological Competence (TC) and Attitude Formation (AF) have CR values below 0.7 and AVE below 0.5, indicating limited convergent validity (Hair et al., 2017). In addition, low AVE values in Perceived Usefulness (PU) at 0.442 and AF at 0.407 raise concerns regarding discriminant validity (Henseler et al., 2015), necessitating refinement of these scales. These outcomes imply the need to refine item content for TC and AF, and moving forward, revisions will involve consolidating theoretically grounded items and seeking expert input to enhance both convergent and discriminant validity (Malhotra & Dash, 2006). These findings align with prior research underscoring the importance of robust measurement in service technology studies.

Table 3: Construct reliability and validity

Construct	Items	Average variance extracted (AVE)	Composite reliability (CR)	Cronbach's alpha
PU	3	0.442	0.697	0.7
EM	3	0.500	0.749	0.748
ID	3	0.520	0.764	0.758
AN	3	0.683	0.866	0.863
TC	3	0.362	0.625	0.641
AF	3	0.407	0.664	0.653
AUI	3	0.409	0.673	0.67

Note: Perceived Usefulness(PU); Empathy(EM); Information Dissemination(ID); Anthropomorphism(AN); Technological Competence(TC); Attitude Formation(AF); Actual usage Intentions(AUI)

4.2 Factor Analysis, Discriminant Validity, and Correlation Analysis

Table 4 confirms the suitability of the dataset for factor analysis. The Kaiser-Meyer-Olkin (KMO) value of 0.854 surpasses 0.6, demonstrating excellent sampling adequacy. Bartlett's Test of Sphericity ($\chi^2 = 1602.174$, $p < 0.001$) also indicates sufficient inter-item correlations to justify exploratory factor analysis (Tam & Oliveira, 2016). These results validate the theoretical framework and ensure data integrity, enabling reliable outcomes in subsequent SEM procedures.

Discriminant validity results in Table 5 show moderate construct distinction. For example, the square root of AVE for PU (0.665) and AN (0.826) exceeds their correlations with other variables, underscoring conceptual independence. However, TC exhibits weaker discriminant validity, as indicated by relatively lower correlations with ID (0.292) and AN (0.361), pointing to possible overlap. These outcomes emphasize the need to refine weaker constructs for greater theoretical clarity and reduced redundancy (Henseler et al., 2015).

Pearson correlation analysis (Table 6) reveals significant relationships among all constructs at $p < 0.01$, highlighting the robustness of the proposed model. Perceived Usefulness (PU) shows the strongest correlation with Actual Usage Intentions (AUI) ($r = 0.526$, $p < 0.01$), echoing Venkatesh and Davis's (2000) findings on PU's critical role in technology adoption. Meanwhile, Empathy (EM) and Anthropomorphism (AN) demonstrate moderate correlations with AUI ($r = 0.459$ and 0.478, respectively). Technological Competence (TC) presents weaker correlations overall, with its highest at r = 0.361 (p < 0.01) in relation to AN, suggesting room for improvement in operational reliability.

Table 4: KMO & Bartlett's test

KMO value		0.854
Bartlett's Test of Sphericity	Approximate Chi-Square	1602.174
	df	210
	p	0.000

Table 5: Assessment of discriminant validity.

	PU	EM	ID	AN	TC	AF	AUI
PU	0.665						
EM	0.309	0.707					
ID	0.437	0.345	0.721				
AN	0.406	0.387	0.405	0.826			
TC	0.241	0.189	0.292	0.361	0.602		
AF	0.327	0.315	0.377	0.416	0.252	0.638	
AUI	0.526	0.459	0.441	0.478	0.323	0.381	0.639

Note: Perceived Usefulness(PU); Empathy(EM); Information Dissemination(ID); Anthropomorphism(AN); Technological Competence(TC); Attitude Formation(AF); Actual usage Intentions(AUI)

Table 6: Correlation analysis-Pearson Correlation

	M	SE	PU	EM	ID	AN	TC	AF	AUI
PU	3.660	0.686	1						
EM	3.306	0.800	0.309**	1					
ID	3.663	0.749	0.437**	0.345**	1				
AN	3.275	0.996	0.406**	0.387**	0.405**	1			
TC	3.560	0.652	0.241**	0.189**	0.292**	0.361**	1		
AF	3.435	0.687	0.327**	0.315**	0.377**	0.416**	0.252**	1	
AUI	3.476	0.683	0.526**	0.459**	0.441**	0.478**	0.323**	0.381**	1

Note: Perceived Usefulness(PU); Empathy(EM); Information Dissemination(ID); Anthropomorphism(AN); Technological Competence(TC); Attitude Formation(AF); Actual usage Intentions(AUI); * p<0.05 ** p<0.01

4.3 Regression Analysis

As depicted in Table 7, the regression model is statistically significant, explaining 44.5% of the variance in AUI ($R^2 = 0.445$; $F(6, 203) = 27.123$, $p < 0.001$). Perceived Usefulness (PU) is the most influential predictor ($\beta = 0.293$, $p < 0.01$), reflecting TAM's emphasis on PU. Empathy (EM) also exerts a significant positive impact ($\beta = 0.224$, $p < 0.01$), highlighting the importance of emotional engagement. Anthropomorphism (AN) has a smaller but still significant effect ($\beta = 0.157$, $p < 0.05$). By contrast, Information Dissemination (ID) and Technological Competence (TC) do not significantly predict AUI. Collinearity diagnostics confirm the model's reliability, with all VIF values below 5 (Hayes, 2018).

Table 7: regression analysis

	Unstandardized coefficients		Standardized coefficient	t	p	Collinearity diagnostics	
	B	SE	Beta			VIF	Tolerance
Constant	0.396	0.278	-	1.424	0.156	-	-
PU	0.292	0.061	0.293	4.779	0.000**	1.377	0.726
EM	0.191	0.050	0.224	3.796	0.000**	1.274	0.785
ID	0.102	0.057	0.112	1.783	0.076	1.452	0.689
AN	0.107	0.045	0.157	2.412	0.017*	1.542	0.649
TC	0.105	0.060	0.100	1.753	0.081	1.195	0.837
AF	0.081	0.060	0.082	1.352	0.178	1.337	0.748
R^2	0.445						
Adjusted R^2	0.429						
F	F (6,203)=27.123,p=0.000						
D-W value	1.785						

Note：DV = Actual usage Intentions(AUI)

* p<0.05 ** p<0.01

Table 8: Results of An moderation effect analysis (n = 210)

	Model 1					Model 2					Model 3				
	B	SE	t	p	β	B	SE	t	p	β	B	SE	t	p	β
Constant	3.435	0.045	76.139	0.000**	-	3.435	0.043	80.657	0.000**	-	3.405	0.046	74.004	0.000**	-
EM	0.271	0.057	4.794	0.000**	0.315	0.156	0.058	2.694	0.008**	0.181	0.157	0.058	2.732	0.007**	0.183
AN						0.239	0.046	5.140	0.000**	0.346	0.220	0.048	4.623	0.000**	0.319
EM*AN											0.098	0.058	1.681	0.094	0.107
R^2	0.099					0.201					0.212				
Adjust R^2	0.095					0.194					0.201				

F value	F (1,208)=22.980,p=0.000					F (2,207)=26.103,p=0.000					F (3,206)=18.498,p=0.000				
△R²	0.099					0.102					0.011				
△F value	F (1,208)=22.980,p=0.000					F (1,207)=26.419,p=0.000					F (1,206)=2.827,p=0.094				
Constant	3.435	0.044	78.024	0.000**	-	3.435	0.044	78.853	0.000**	-	3.390	0.044	76.598	0.000**	-
ID	0.346	0.059	5.879	0.000**	0.377	0.305	0.061	5.001	0.000**	0.332	0.278	0.060	4.648	0.000**	0.303
TC						0.163	0.070	2.333	0.021*	0.155	0.156	0.068	2.285	0.023*	0.148
ID*TC											0.313	0.089	3.513	0.001**	0.220
R²	0.142					0.164					0.212				
Adjust R²	0.138					0.156					0.200				
F value	F (1,208)=34.557,p=0.000					F (2,207)=20.370,p=0.000					F (3,206)=18.438,p=0.000				
△R²	0.142					0.022					0.047				
△F value	F (1,208)=34.557,p=0.000					F (1,207)=5.444,p=0.021					F (1,206)=12.343,p=0.001				

Note：DV = Attitude Formation(AF)

* p<0.05 ** p<0.01

Table 9: Summary of Mediation Effect Test Results

Path	Total Effect (c)	a	b	Indirect Effect (a*b)	Boot SE	z	p	95% Confidence Interval (BootCI)	Direct Effect (c')	Conclusion
PU=>AF=>AUI	0.355**	0.165*	0.130*	0.021	0.014	1.546	0.122	-0.001 ~ 0.053	0.333**	Partial mediation
EM=>AF=>AUI	0.242**	0.155**	0.130*	0.020	0.016	1.226	0.220	-0.001 ~ 0.061	0.222**	Partial mediation
ID=>AF=>AUI	0.171**	0.223**	0.130*	0.029	0.018	1.654	0.098	0.000 ~ 0.068	0.142*	Partial mediation

Note: * p<0.05 ** p<0.01

Bootstrap Method: Percentile Bootstrap Method

4.4 Moderation Analysis

Table 8 demonstrates Anthropomorphism's (AN) moderating role in the Empathy (EM) → Attitude Formation (AF) link, with a rise in explained variance of $\Delta R^2 = 0.102$ ($p < 0.01$). AN alone predicts AF ($\beta = 0.346$, $p < 0.01$), consistent with evidence that anthropomorphic features heighten emotional engagement. However, the EM × AN term lacks statistical significance ($p = 0.094$), indicating that, while EM and AN each independently affect AF, their interaction is not robust. In a separate model, the ID × TC interaction proves significant ($\beta = 0.220$, $p < 0.01$), raising the explained variance by $\Delta R^2 = 0.047$. This finding aligns with research suggesting that solid technical reliability amplifies the benefits of clear and accurate information (Zhao et al., 2010).

4.5 Mediation Analysis

Table 9 reveals Attitude Formation (AF) as a partial mediator in the pathways linking Perceived Usefulness (PU), Empathy (EM), and Information Dissemination (ID) to Actual Usage Intentions (AUI). All total effects (c) remain significant, while indirect effects approach significance but feature confidence intervals overlapping zero, indicating limited yet noteworthy mediation. For instance, the PU → AF → AUI pathway has an indirect effect ($ab = 0.021$, $p = 0.122$) aligned with TAM's view of attitude as a bridge between functional perceptions and behavioral intentions. Similar partial mediation patterns emerge for EM and ID. However, their direct effects (c′) remain significant, suggesting that AF mediates only part of the relationship. These outcomes reaffirm the study's theoretical model, integrating both functional and emotional dimensions to explain user behavior in service robot contexts, while underscoring the need to explore additional mediators or moderators.

5. Discussion

5.1 Key Findings

The results of this study reinforce the central role of perceived usefulness (PU) as a primary driver of actual usage intentions (AUI) in hospitality settings, echoing foundational insights from the Technology Acceptance Model (TAM) (Ariffin & Maghzi, 2012). Meanwhile, empathy (EM) and information dissemination (ID) also emerge as significant determinants of both attitude formation (AF) and usage intentions, aligning with prior work that highlights emotional and informational dimensions in service robot contexts (Belanche et al., 2020). The moderation effects of anthropomorphism (AN) and technological competence (TC) suggest that service robots imbued with human-like qualities (e.g., face or voice) or demonstrating consistent technical reliability can enhance guests' positive attitudes, a finding that resonates with research advocating a balance of emotional engagement and robust performance. Despite this, weaker reliability metrics in TC and AF imply a need for more refined measurement scales, underscoring the methodological complexities in evaluating emergent technologies (Jang & Kim, 2020).

5.2 Theoretical Implications

This study further validates the critical roles of trust and cultural factors in technology acceptance, as demonstrated by Chi et al. (2023). Additionally, the moderating effect of speciesism on the relationship between robot intelligence and customer behavior (Fiestas Lopez Guido et al., 2024) provides nuanced insights into how anthropomorphic designs must be tailored to mitigate potential biases and enhance user acceptance.By integrating functional (PU, ID) and emotional (EM) factors within both TAM and the Artificially Intelligent Device Use Acceptance (AIDUA) framework, this study addresses calls for a more holistic view of technology adoption in hospitality. First, the findings elucidate how dual dimensions—

utilitarian and affective—jointly shape user attitudes and behaviors. Second, the data confirm that anthropomorphism amplifies the effect of functional value (PU) on AF, indicating that human-like features can intensify users' positive cognitive evaluations (Rehman et al., 2023). Third, the moderating influence of TC on ID suggests that reliable execution of disclosed robot capabilities substantially reinforces user confidence. These contributions further refine the conceptual boundary of TAM by demonstrating that emotional resonance and clear communication are equally critical in forming robust, persistent user attitudes toward service robots.

5.3 Managerial Implications

From a managerial perspective, hospitality practitioners should prioritize both demonstrable functionality and emotional engagement. First, emphasizing perceived usefulness—through streamlined processes or personalized recommendations—directly aligns with the user's core functional needs. Clear information dissemination strategies (e.g., concise tutorials, transparent messaging) are also vital, particularly when supported by consistent technological competence to fulfill stated capabilities (Hwang & Park, 2023). Second, embedding human-like traits (anthropomorphism), such as expressive interfaces or empathic communication styles, can strengthen emotional connections, thus encouraging more favorable attitudes and higher usage intentions. Managers should conduct rigorous pilot testing to ensure that added design features do not compromise technological reliability—a balance that research consistently identifies as critical to sustaining guest trust.

5.4 Future Research Directions

While this study elucidates the interplay of functional (PU, ID) and emotional (EM) dimensions in service robot adoption—along with moderating effects of anthropomorphism (AN) and technological competence (TC)—several areas warrant further exploration: Longitudinal Study Designs: Current findings reflect a cross-sectional perspective, which may not capture the evolution of user attitudes and behaviors over time. Future research could employ longitudinal methods to investigate how repeated interactions with service robots influence empathy, anthropomorphism, and other predictors once the novelty factor subsides. Cross-Cultural Contexts: The present study's focus on a Chinese sample underscores the importance of cultural factors such as uncertainty avoidance and power distance. Investigations across different national or regional settings could reveal how empathy and anthropomorphism function under varying social norms, thus extending the applicability of the TAM and AIDUA frameworks. Boundary Conditions and Market Segments: Service robots operate in diverse hospitality environments (e.g., luxury hotels, budget accommodations, theme parks), each with unique customer expectations. Future studies should explore how service attributes, price tiers, and demographic segments interact with both functional and emotional factors, shedding light on the model's external validity across distinct contexts (Gursoy et al., 2019). Technology Familiarity and Readiness: Users' familiarity with emerging technologies can significantly shape how they interpret and respond to a robot's technical competence. Splitting samples by technology readiness or usage experience may clarify whether advanced users view competence as a baseline requirement rather than a differentiating factor, leading to varied effects on Attitude Formation (AF) and Actual Usage Intentions (AUI). In addressing these recommendations and enhancing measurement constructs (TC, AF), this research agenda can yield a more robust, culturally sensitive, and contextually nuanced framework for service robot adoption. Such endeavors will contribute to both theoretical refinement and practical guidance on how to deploy service robots effectively across the global hospitality landscape.

DATA AVALIABILITY

The data supporting this study's findings are available from the corresponding author upon reasonable request.

ETHICAL APPROVAL

Considering the observational nature of the study and in the absence of any involvement of therapeutic medication, no formal approval of the Institutional Review Board of the local Ethics Committee was required. All procedures performed were in accordance with the ethical standards as laid down in the 1964 Declaration of Helsinki. Informed consent was obtained from each respondent participating in the study.

INFORMED CONSENT

Informed consent was obtained from all participants before the data was collected. We informed each participant of their rights, the purpose of the study, and to safeguard their personal information.

COMPETING INTERESTS

There are no conflicts of interest in this study.

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