



Dining with robots: An integrated perspective on functional, emotional and relational dimensions of customer experience

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Abstract

As service robots become increasingly embedded in hospitality settings, especially restaurants, understanding how customers experience and respond to these technologies is essential for advancing theory and informing design. This study examines how functional, emotional and relational dimensions jointly shape customer satisfaction and revisit intentions in the context of non-humanoid, task-oriented robots. Addressing gaps in existing adoption-focused models, the research integrates the stimulus–organism–response (S–O–R) framework with the USUS model to investigate how constructs such as service efficiency, enjoyment, friendliness, trust and rapport influence post-adoption engagement. Using data from 308 real-world restaurant customers and analysed through partial least squares structural equation modelling (PLS–SEM), the study explores both mediation and moderation pathways, including the roles of rapport and individual novelty-seeking tendencies. This work contributes to the human–robot interaction (HRI) and service marketing literature by shifting focus from humanoid social mimicry to functional robotic design’s affective and relational potential. The findings explain how emotional connection, operational performance and psychological traits shape sustained customer engagement with robotic services. Implications are offered for designing customer-centric, socially acceptable and operationally effective robot experiences in high-contact service environments.

Keywords Service robots · Human-robot interactions (HRI) · Customer engagement · Rapport and trust · Novelty-seeking behaviour · Stimulus-organism-response (S-O-R) · USUS framework

Introduction

The integration of service robots in the hospitality industry is reshaping customer experiences, particularly in restaurant environments. These robots provide efficiency, consistency

and scalability, making them essential for operational optimisation (Ivanov et al., 2020; Jörling et al., 2019). However, their increasing presence introduces critical trade-offs between functional efficiency and the human-centric service qualities that define hospitality (Kim et al., 2021; Mende et al., 2019). While robotic service adoption enhances operational performance, long-term customer satisfaction and loyalty require a broader understanding of how functional, emotional and relational factors collectively influence customer experiences (Ali et al., 2024; Balaji et al., 2025). The challenge lies in determining how these dimensions interact, and shape sustained engagement with robotic services (Tuomi et al., 2021).

Gaps in existing research

Much of the literature on technology adoption has been shaped by utilitarian frameworks such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT)

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(Venkatesh et al., 2003), which emphasise perceived usefulness and ease of use as primary drivers of adoption. While these models offer valuable insights into initial acceptance, they provide limited explanation for sustained engagement, particularly in emotionally and socially rich service contexts such as hospitality (Cronin et al., 2000; Qiu et al., 2020). Existing studies have largely focused on the functional benefits of service robots, highlighting usability, reliability and performance efficacy (Song & Kim, 2022), yet empirical investigations into the emotional and relational dimensions of human–robot interaction (HRI) remain scarce (Hu, 2021). Furthermore, much of this research has been conducted in artificial or experimental settings, limiting its relevance to real-world customer experiences and long-term behavioural responses to robotic services.

Another limitation in current research is the predominant focus on anthropomorphic or humanoid robots when examining emotional and relational constructs such as friendliness, trust and rapport. While humanoid designs may heighten perceived warmth or sociability, they are not representative of most service robots currently deployed in commercial environments, particularly in sectors like food delivery or retail (Huang & Liu, 2022). Non-humanoid robots, which are primarily task oriented and designed for efficiency rather than human resemblance, remain understudied in terms of how they elicit emotional and relational responses from customers. Understanding how such robots influence satisfaction and revisit intentions is important as businesses increasingly adopt non-humanoid solutions that do not rely on humanlike form to deliver service value (Cha et al., 2018).

In addition, sustaining customer engagement beyond initial novelty remains a persistent challenge. Robotic services often attract early attention but may struggle to maintain interest over time, especially among high novelty seeking individuals who rapidly adapt to new stimuli (El-Said & Al Hajri, 2022; Kim et al., 2022a, 2022b; Sung et al., 2016). The role of rapport in robotic service interactions further complicates this landscape. While rapport is well established as a driver of satisfaction in human delivered services (Gremler & Gwinner, 2000), its function in robotic contexts appears to be more ambiguous, potentially amplifying friendliness while moderating the impact of trust (Nomura & Kanda, 2016; Song et al., 2022a, 2022b).

These gaps point to the need for a more comprehensive framework that moves beyond utilitarian predictors to consider how functional, emotional and relational stimuli shape customer experiences with service robots, particularly in real world settings involving non-humanoid agents. Addressing these gaps is important for advancing theoretical understanding of sustained customer engagement and informing the design and deployment of service robots capable of fostering long term loyalty in automated service environments.

Research objectives and contributions

To address the limitations of existing models that focus predominantly on initial adoption, this study draws on the stimulus–organism–response (S–O–R) framework (Mehrabian & Russell, 1974) in conjunction with the USUS model (Weiss et al., 2009) to propose a more comprehensive approach to understanding customer experience in HRI settings. By examining how functional (e.g. usability, efficiency), emotional (e.g. friendliness, novelty) and relational (e.g. trust, rapport) dimensions influence key post-adoption outcomes such as satisfaction and revisit intention, the study offers a more complete perspective on customer engagement with service robots. In doing so, it also considers the role of psychological moderators, specifically rapport and individual novelty-seeking tendencies, that may shape or condition these effects over time. These contributions aim to extend current theorisation in both HRI and service marketing by (i) integrating functional, emotional, and relational stimuli into a unified explanatory model; (ii) incorporating psychological boundary conditions that may explain differential customer responses; and (iii) advancing understanding of the mechanisms through which customer retention evolves in response to robot-delivered services.

Introduction to HRI

Classifying service robots

Service robots can be categorised based on their functional roles and levels of interactivity, ranging from task-oriented functional robots to socially engaging relational robots. Functional robots are primarily designed for efficiency and precision, executing specific tasks with minimal human interaction (Karabegović et al., 2021; Chang & Kim, 2022). In contrast, transactional robots engage in simple, rule-based interactions, such as automated check-in services or self-service kiosks, while relational robots are developed to facilitate social engagement through both verbal and non-verbal communication (Park & Jung, 2024). These distinctions show the varying degrees of interactivity across different robot types. Table 1 provides a detailed classification of service robots, outlining their key characteristics, examples, and interactivity levels to illustrate these variations.

Functional service robots and the role of experiential cues

HRI research has long emphasised the advantages of anthropomorphism, suggesting that human-like characteristics foster warmth, trust, and likability (Huang et al., 2021; Lin & Mattila, 2021; Ogan, 2024). However, this approach is

Table 1 Classification of service robots based on interactivity

Category	Definition	Key characteristics	Examples	Comparison with other categories	Interactivity level
Functional robots	Perform specific, often repetitive tasks with high efficiency	■ Operate with minimal communication with humans (Karabegović et al., 2021; Park & Jung, 2024) ■ Focus on task precision in well-structured environments (Zieliński et al., 2007) ■ Prioritise task efficiency over interaction, focusing on labour methods rather than communication levels (Chang & Kim, 2022)	Cleaning robots, remote-controlled communication robots, transport robots in hospitals, automated check-in kiosks (Graf et al., 2013; Park & Jung, 2024)	■ Less interaction with humans than transactional, relational, and cognitive robots (Chang & Kim, 2022) ■ Focused solely on task efficiency rather than relational or cognitive aspects (Karabegović et al., 2021; Park & Jung, 2024)	Low: Perform simple, repetitive tasks with minimal human interaction. The primary focus is on efficiency and reliability
Hybrid-functional robots	Perform specific service tasks with minimal but structured social interaction to improve engagement	■ Primarily task-oriented but integrates limited interactive components (e.g. screen-based expressions, voice prompts, polite acknowledgments) ■ Designed to enhance customer engagement through structured interaction rather than relational bonding (Shin, 2022) ■ Operate in well-structured environments and focus on efficiency with subtle social cues	Service robots in restaurants (e.g. delivery robots with verbal acknowledgments, interactive touchscreen ordering systems)	■ More interactive than purely functional robots but lack the deep social engagement of relational robots ■ Unlike transactional robots, hybrid-functional robots emphasise service execution over simple rule-based transactions	Low-to-Medium: Primarily efficiency-driven but incorporate basic interactive engagement features
Transactional robots	Engage in simple, structured interactions to complete transactions	■ Designed for tasks such as service delivery and guidance systems (Karabegović et al., 2021) ■ Moderate communication with humans Park and Jung, (2024)	Check-in/out robots in hotels, ordering kiosks, delivery robots (Zieliński et al., 2007)	■ More interaction with humans than functional robots but less than relational and cognitive robots (Chang & Kim, 2022) ■ Prioritise structured, rule-based interactions for specific service tasks (Chang & Kim, 2022; Park & Jung, 2024)	Medium: Engage in basic transactional interactions, requiring structured inputs and providing specific outputs

Table 1 (continued)

Category	Definition	Key characteristics	Examples	Comparison with other categories	Interactivity level
Relational robots	Designed to build and maintain relationships with users through social interactions	- Engage in relational tasks with higher levels of communication (Park & Jung, 2024) - Promote customer satisfaction through perceptions of warmth and communal relationship alignment (Chang & Kim, 2022)	Emotional robots used for therapeutic or entertainment purposes, concierge robots, service robots in restaurants (Park & Jung, 2024)	- Focus on social presence and warmth, unlike functional robots - Greater emphasis on communication compared to transactional robots - Less reliance on cognitive reasoning than cognitive robots (Chang & Kim, 2022)	High: Engage in verbal and non-verbal communication, provide personalised services, and maintain rapport with customers
Cognitive Robots	Exhibit advanced cognitive abilities, capable of learning and adapting to new environments	- Operate in unstructured environments with high levels of sensing, reasoning, and adaptability (Zielinski et al., 2007) - Designed for cognitive tasks with close cooperation with humans (Park & Jung, 2024)	AI robots with scene classification capabilities, advanced robots like <i>Sophia</i> developed by Hanson Robotics (Chang & Kim, 2022)	- Most advanced in terms of communication and adaptability - Differ from functional robots by operating in dynamic, unstructured environments - Rely on reasoning and adaptability more than relational or transactional robots (Chang & Kim, 2022; Zielinski et al., 2007)	Very High: Engage in meaningful, adaptive conversations, detect emotions, and demonstrate advanced AI capabilities

less applicable to the growing class of non-humanoid service robots, particularly in sectors such as hospitality and food service, where robots are designed not to resemble humans but to execute tasks with precision, consistency, and speed (Goetze et al., 2012; Cha et al., 2018). As classified in Table 1, these functional or hybrid-functional robots are task-oriented, engineered to perform specific service roles, such as food delivery or order handling, with minimal or structured human interaction. Unlike relational or cognitive robots, their effectiveness is evaluated by usability, efficiency and reliability, rather than emotional mimicry or social bonding (Chang & Kim, 2022; Park & Jung, 2024).

Despite their low interactivity level, non-humanoid robots are not devoid of experiential value. Increasing evidence shows that carefully designed interface elements, such as polite voice prompts, responsive gestures or cheerful tones, can positively influence customer perceptions (Shin, 2022). These design features help to humanise task-focused robots, making interactions feel smoother and more engaging. Functional robots that exhibit such characteristics can evoke customer satisfaction not only through task performance but also through subtle emotional engagement (Huang & Liu, 2022; Tussyadiah et al., 2020).

Two constructs are especially salient in this context: friendliness and rapport. Functional robots can express friendliness through simple, nonverbal features such as welcoming tones, polite phrasing and intuitive responsiveness (Huang et al., 2021). Even without anthropomorphic form, such cues can shape positive attitudes, enhance likability and reinforce brand perceptions (Oğan, 2024; Rana et al., 2025). Friendliness thus operates as a low-effort affective cue that improves perceived service quality and contributes to higher customer satisfaction (Tussyadiah et al., 2020; Shin, 2022).

Rapport, originally conceptualised in human service encounters as mutual attentiveness and connection (Grewler & Gwiner, 2000), has been adapted to HRI to capture how customers perceive the warmth and responsiveness of service robots. While anthropomorphic robots build rapport through emotional displays and social mimicry, functional robots achieve rapport differently, i.e., primarily through task reliability, efficiency and interactional smoothness (Hlee et al., 2022). For example, a delivery robot that communicates clearly, operates seamlessly and maintains consistency in service delivery can foster a sense of rapport even without emotional intelligence or deep social engagement. This task-based rapport plays a role in elevating satisfaction and encouraging customers to perceive the service encounter as competent and pleasant.

Importantly, although both friendliness and rapport are traditionally associated with socially intelligent robots, their application in functional and hybrid-functional robots is gaining recognition. These constructs offer a way to bridge the gap between cold efficiency and engaging service, particularly in contexts where full anthropomorphism is not viable

or necessary. However, empirical research remains limited in this area, and the mechanisms through which experiential cues operate in non-humanoid service settings are still underexplored. As the deployment of task-oriented robots accelerates, particularly in high-contact industries like food service, it becomes increasingly important to understand how customers experience not only the functionality but also the subtle relational aspects of robotic service delivery.

Theoretical foundations: S–O–R and USUS frameworks

The S–O–R framework (Mehrabian & Russell, 1974) provides a foundational model for explaining how external stimuli trigger internal cognitive or emotional states, which in turn drive behavioural responses. Originally developed in environmental psychology, S–O–R has been widely applied in consumer behaviour, service management and technology adoption research to explain customer decision-making processes (Cronin et al., 2000; Zhu et al., 2020). This study extends the S–O–R framework in the context of HRI by focusing on three key dimensions of service robot experience—functional, emotional and relational—as the salient stimuli influencing customer satisfaction and behavioural responses. These dimensions represent distinct aspects of robotic service encounters and are conceptualised as follows:

- **Functional dimension:** Emphasises the robot's usability, efficiency and performance reliability, which together influence the customer's perception of service effectiveness (Chopdar & Balakrishnan, 2020). This includes attributes like consistent responsiveness and error-free operation that ensure the robot performs its tasks safely and reliably.
- **Emotional dimension:** Covers the affective responses elicited by the robot, such as the novelty of the interaction, the robot's friendliness and the enjoyment the customer feels during the encounter. These emotional factors shape the customer's overall satisfaction and attitude toward the service robot (Tussyadiah et al., 2020).
- **Relational dimension:** Encompasses the sense of trust and rapport that can develop between the customer and the service robot. This relational connection influences how reliable the customer perceives the robot to be and the customer's willingness to engage with it in a social or service context (Gremler & Gwinner, 2000; Song & Kim, 2022).

However, while the S–O–R framework describes the process by which stimuli lead to internal states and responses, it does not explicitly classify the nature of those stimuli or

how users interpret their interactions with robots. To address this gap, we integrate the USUS framework (Rana et al., 2025; Weiss et al., 2009) into our theoretical approach. USUS (an acronym for Usability, Social Acceptance, User Experience, and Societal Impact) offers a rounded, user-centric lens for evaluating human–technology interactions (Rana et al., 2025). Originally introduced in the HRI literature (Rana et al., 2025; Weiss et al., 2011), the USUS framework delineates four complementary dimensions for assessing user experience and system acceptance. In our integrated S–O–R–USUS framework, each of the first three USUS dimensions aligns with one of the core aspects of service robot experience identified above:

- **Usability** corresponds to the functional dimension of the robotic service. It captures the ease of use, efficiency, and safety of the robot's performance. Essentially, how well the robot's functional attributes meet customers' needs (e.g. smooth navigation and error-free task execution).
- **Social Acceptance** maps onto the relational dimension, reflecting the customer's willingness to accept the robot as a social interaction partner. This includes interpersonal factors such as the trustworthiness of the robot and the level of rapport or comfort the customer feels when interacting with it.
- **User Experience** aligns with the emotional dimension, encompassing the affective quality of the interaction. It reflects how engaging, enjoyable or novel the robot encounter is for the customer, including perceptions of the robot's friendliness and the excitement of using a new technology.

(The USUS framework's fourth component, Societal Impact, involves broader social and ethical implications of robotics. While important, this aspect lies beyond the scope of our immediate focus on individual customer experiences.)

As summarised in Table 2, applying the USUS framework to our model provides a structured categorisation of the functional, relational and emotional stimuli dimensions and their key constructs. This structured focus allows for a more precise evaluation of how customers interpret and evaluate service-robot interactions in hospitality settings. Integrating S–O–R and USUS in this way yields a comprehensive theoretical foundation for understanding customer experiences with service robots. The S–O–R framework explains the causal sequence by which robot attributes (stimuli) evoke internal evaluations and drive outcomes, while the USUS framework defines the content of those evaluations and how customers judge the robot on multiple criteria (Weiss et al., 2009; Zhu et al., 2020).

This dual-framework approach also extends prior technology-adoption research, which predominantly emphasised utilitarian factors (e.g. usefulness, ease of use) and

initial adoption decisions (Davis, 1989; Venkatesh et al., 2003). Traditional models like the TAM and the UTAUT are mainly on early adoption drivers (Davis, 1989; Venkatesh et al., 2003) and tend to overlook the evolving, experiential aspects of long-term use. In contrast, the integrated approach of current study considers how *sustained* engagement factors, such as the fading novelty of interacting with a robot over time or the gradual development of rapport between customer and robot, can influence ongoing customer satisfaction and continued patronage intention. This perspective helps bridge the gap between initial acceptance of service robots and the customer experience as interactions continue and evolve.

Hypotheses development

Building on the S–O–R framework, this study identifies functional, emotional and relational dimensions as key stimuli shaping customer responses to robotic service interactions (Zhu et al., 2020; Rajput & Gahfoor, 2020). Prior research in human-centric hospitality settings has examined these dimensions separately (Bartneck et al., 2009; Wirtz et al., 2018), but their integrated influence in robotic settings remains underexplored. Functional attributes, such as perceived safety, service efficiency and performance efficacy, shape usability perceptions and build trust in the service (i.e. confidence that the service will be delivered reliably) (Chopdar & Balakrishnan, 2020; Ivanov et al., 2020). Emotional attributes (e.g. novelty, enjoyment, friendliness) enrich the user experience, although their impact may diminish over time as customers acclimate to the novelty (Tung & Au, 2018; Ghazali et al., 2020; El-Said & Al Hajri, 2022). Relational attributes, especially trust, facilitate social acceptance by giving customers a sense of security during human–robot interactions (Kim et al., 2022a, 2022b; Tusyadiah et al., 2020). In addition, two psychological factors, customer–robot rapport and customers’ novelty-seeking tendency, are considered as moderators that can alter the strength of these relationships over time (Nomura & Kanda, 2016). Based on these theoretical foundations, a series of hypotheses is developed to predict how the identified stimuli influence customer satisfaction, attitude, and behavioural intentions (specifically, revisit intention).

The mediating effects of attitude

Within the S–O–R model, a service robot’s functional features are processed cognitively by the customer and can shape the customer’s attitude toward the service (Park & Pobil, 2013). Perceived safety is defined as the customer’s impression of the risk of interacting with a robot and their

degree of comfort with the robot (Bartneck et al., 2009). High perceived safety includes both physical safety and reduced fear of robotic errors (e.g. not worrying that the robot might cause harm) (Wirtz et al., 2018). This sense of safety is crucial for acceptance of robotic services: customers are more willing to interact with robots when they feel safe and comfortable doing so (Tung & Law., 2017). Empirical studies find that when customers believe a robot is safe, they tend to form a more positive attitude toward using it (Hlee et al., 2022). In other words, reducing concerns about mistakes or harm fosters a favourable view of the robot. Formally, it is hypothesised that:

H1a. Attitude positively mediates the relationship between perceived safety and customer’s intention to revisit a restaurant with robotic service.

Service efficiency, that is the ability of the service (robot + staff) to minimise wait times and maximise productivity, is another functional stimulus expected to influence attitudes. Efficient use of robots can speed up service delivery, as evidenced by reduced waiting times and increased productivity in robot-assisted settings (Vatan & Doğan., 2021). For example, faster service (such as quicker reservations or payments) has been linked to higher customer satisfaction in online service contexts (Gomes Furtado et al., 2019). In a restaurant, customers may be impressed by robots that deliver orders promptly, enhancing their attitude toward the service (El-Said & Al Hajri, 2022). If robots fail to provide efficiency gains, however, their added value is questionable (Byrd et al., 2021). Thus, efficiency improvements via robotics should translate into more positive customer attitudes, which then encourage return visits. Hence:

H1b. Attitude positively mediates the relationship between service efficiency and customer’s intention to revisit a restaurant with robotic service.

The performance efficacy of service robots, that is how well they execute their tasks, further contributes to functional value. Performance efficacy includes reliability, speed, and consistency in task performance (Tojib et al., 2022). Unlike human workers, robots can operate continuously and perform repetitive jobs without fatigue, potentially outperforming humans on routine tasks (Ivanov et al., 2020). Technological advances (e.g. in AI and speech recognition) have improved robots’ capabilities, both functionally and even emotionally (to a limited extent) (Go et al., 2020; Murphy et al., 2019). When customers perceive that a robot performs its job well and delivers a positive service experience, they are likely to develop a favourable attitude

Table 2 USUS framework, dimensions and conditional factors

USUS framework factors			Dimensions	Key constructs	Description	Key references
Usability	Functional	Perceived Safety, Service Efficiency, Performance Efficacy	Task-related attributes defining a robot's effectiveness. Customers evaluate service robots based on perceived safety (trust in risk-free operation), service efficiency (speed and effectiveness), and performance efficacy (accuracy and consistency). These functional attributes influence cognitive responses such as attitude and satisfaction, which shape revisit intentions	Weiss et al. (2009); Hlee et al. (2022)		
Social acceptance	Relational	Perceived Trust, Rapport	Represents customer comfort in interacting with robots. Trust is critical for robotic service acceptance, particularly for non-humanoid, task-oriented robots. Rapport moderates trust's effect, as excessive relational engagement from robots may reduce trust if perceived as unnatural	Weiss et al., (2009); Song & Kim (2022)		
User experience	Emotional	Perceived Novelty, Perceived Enjoyment, Perceived Friendliness	Emotional and cognitive evaluations of robotic interactions. Novelty excites customers initially but may lead to diminishing satisfaction over time. Enjoyment and friendliness enhance emotional connection, fostering positive attitudes. However, emotional engagement alone is insufficient without functional reliability and trust	Weiss et al., (2009); Tussyadiah et al., (2020); Oğan (2024); Gocłowska et al., (2019)		
Social impact	Broader implications	Customer Loyalty, Societal Acceptance (Attitude, Satisfaction, Intention to Revisit)	Examines the broader implications of robotic services on customer loyalty and their integration into society. The long-term success of robotic services depends on sustained engagement beyond novelty-driven interactions	Weiss et al., (2009) Rana et al., (2025)		
Moderating factors	Psychological influences on perception	Novelty-Seeking (Moderator—Personality/trait) Rapport (Moderator—Relational factor)	Novelty-seeking behaviour affects how customers engage with novelty, enjoyment and friendliness, aligning with diminishing marginal utility theory—where repeated exposure reduces excitement. Rapport moderates trust's effect on satisfaction; while some rapport enhances engagement, excessive relational interactions from robots may reduce trust	Gocłowska et al., (2019); Kim et al., (2022)		

(Bartneck et al., 2007). A stronger customer attitude, in turn, increases the likelihood of returning to the restaurant. Therefore, it is expected that:

H1c. Attitude positively mediates the relationship between performance efficacy and customer's intention to revisit a restaurant with robotic service.

Taken together, H1a–H1c posit that each functional stimulus (safety, efficiency, efficacy) influences revisit intentions indirectly by first shaping the customer's attitude toward the robot service. A positive attitude serves as a mediating organismic response that carries the effect of functional qualities forward to the behavioural outcome.

The mediating effects of satisfaction

In this study, customer satisfaction represents a key organismic response in the S–O–R framework, mediating the influence of emotional and relational dimensions of HRI on behavioural outcomes. While functional factors are important for basic service quality, emotional engagement often plays a decisive role in sustaining positive perceptions in robotic restaurants. One primary emotional driver in HRI is perceived novelty—the sense of newness or uniqueness in interacting with robotic servers. Novel experiences tend to spark initial excitement, making a service encounter more memorable and engaging (Qiu et al., 2020). However, novelty alone may not guarantee repeat patronage; its effect is largely channelled through satisfaction, which then shapes whether the customer intends to return (Albaity & Melhem, 2017). In a robotic restaurant context, a customer who finds the experience novel is likely to report higher satisfaction, and that heightened satisfaction subsequently increases their intention to revisit. Thus:

H2a. Satisfaction positively mediates the relationship between perceived novelty and customer's intention to revisit a restaurant with robotic service.

Another crucial emotional stimulus is perceived enjoyment—the pleasure and positive affect a customer derives from the interaction with robot servers. Enjoyment captures the intrinsic fun or entertainment value of the experience (beyond just the novelty) and can stem from factors such as an intuitive interaction, engaging robot personality or the high-tech appeal of the service (Davis, 1989; Venkatesh, 2000). Past technology adoption research suggests that enjoyable interactions improve overall user experience, leading to greater engagement and long-term satisfaction (Ghazali et al., 2020; Saari et al., 2022). In

robotic dining, if customers find the service enjoyable, for instance, due to smooth interactions, amusing features or ease of use, they are more likely to feel satisfied; that satisfaction then translates into a stronger intention to return. Accordingly, the following is proposed:

H2b. Satisfaction positively mediates the relationship between perceived enjoyment and customer's intention to revisit a restaurant with robotic service.

Perceived friendliness of the robot is a relationally oriented stimulus that can also enhance satisfaction. In non-humanoid service robots (the kind often used for food delivery in restaurants), 'friendliness' is conveyed through limited but meaningful social cues, for example, polite language in voice prompts, courteous acknowledgments or simple interactive displays (smiling icons, lights, etc.) (Hlee et al., 2022; Shin, 2022). These robots are primarily task-oriented, lacking advanced emotional intelligence or human-like conversation, so customers judge their friendliness based on structured interactions such as polite behaviour, accuracy in service execution and smooth non-verbal cues (Hwang et al., 2020). Even minimal social warmth in a robotic encounter can foster ease and approachability, making customers feel more comfortable and leading to higher satisfaction (Tussyadiah et al., 2020). When task-focused robots exhibit friendly gestures (clear communication, timely service, polite responses), customers tend to perceive the interaction positively, which reinforces both enjoyment and trust in the service (Groom et al., 2010; Pugh, 2001). In robotic restaurant settings, these positive emotional responses elevate overall satisfaction, thereby strengthening the likelihood of customers returning. Formally:

H2c. Satisfaction positively mediates the relationship between perceived friendliness and customer's intention to revisit a restaurant with robotic service.

Beyond emotional factors, a key relational stimulus is trust in the robot-delivered service. Trust here refers to the customer's confidence in the robot's reliability, competence and integrity in performing its service role (Gaudiello et al., 2016). In technology-mediated interactions, trust is critical for comfort because it reduces uncertainty and anxiety about the service encounter (Tussyadiah et al., 2020). When customers trust a robotic server, believing it will function as intended and not fail unexpectedly, they are more at ease and more satisfied with the experience (Hwang et al., 2020). Prior studies in hospitality robotics show that trust can mitigate the perceived risk of autonomous services, thereby

increasing satisfaction and the willingness to use such services (and return) (Tussyadiah et al., 2020). Thus, it is hypothesised that:

H3. Satisfaction positively mediates the relationship between perceived trust and customer's intention to revisit a restaurant with robotic service.

In sum, H2a–H2c and H3 propose that emotional stimuli (novelty, enjoyment, friendliness) and a relational stimulus (trust) each influence revisit intentions via the intermediary of customer satisfaction. A satisfying robot-service encounter is expected to translate these experiential and relational benefits into a greater likelihood of returning.

Sequential mediation of satisfaction and attitude

While satisfaction and attitude are both important organismic responses in the S–O–R model, they are conceptually distinct. Satisfaction is an affective, episode-specific response. It is the customer's contentment with a particular service encounter. Attitude on the other hand is a more enduring evaluation of the service (or provider) on a favourable–unfavourable continuum (Oliver, 1993). It is theorised that these two responses can form a sequence: a positive immediate experience (satisfaction) can improve the customer's overall attitude toward the service, which in turn drives their behavioural intention to return (Oliver, 1999). A satisfying robot interaction updates the customer's general evaluation of the restaurant (making it more positive), and a favourable attitude is well-known to predict repeat patronage. Thus, after a satisfying encounter, the customer's strengthened attitude toward the robot-assisted restaurant becomes a key driver of the decision to revisit (Kim & Qu, 2014).

Not all stimuli will trigger this satisfaction → attitude → intention chain equally. It is expected that this sequential mechanism operates primarily for emotional and relational stimuli, rather than for purely functional ones. Emotional and relational cues (novelty, enjoyment, friendliness, trust) directly engage customers' feelings and social perceptions. For example, a novel interactive feature can excite and delight, and a friendly, trustworthy robot can foster a personal bond. Such stimuli tend to heighten affective satisfaction and subsequently shape a more favourable attitude. In contrast, functional attributes like efficiency or safety, while important, mostly fulfil baseline utilitarian expectations. Meeting these expectations can yield satisfaction, but often on a more cognitive level (e.g. 'the service was quick, so I'll come back') that might influence revisit intention directly, rather than by fundamentally changing one's long-term attitude. In other words, functional performance alone might prompt repeat business out of practical

convenience without necessarily enhancing the customer's overall affinity toward the service (Brunner-Sperdin et al., 2012; Falk et al., 2010). Emotional and social stimuli, however, provide the kind of positive affective experience that can both satisfy the customer and bolster their attitude toward the robot service. This reasoning aligns with findings that purely cognitive evaluations (e.g. perceived usefulness, innovativeness) can drive acceptance intentions even without strong emotional responses, indicating that when emotional satisfaction is present it plays a special role in also shaping attitudes (Chen & Girish, 2023; Sung & Jeon, 2020).

A serial mediation process is proposed in which certain stimuli influence revisit intention through a two-step path: first through satisfaction, and then through attitude (satisfaction feeding into attitude). This is consistent with the S–O–R framework's view of multiple internal states linking stimuli to responses. Accordingly:

H4a–d. Satisfaction and attitude sequentially mediate the positive relationships between HRI stimulus-*perceived novelty, enjoyment, friendliness, trust*-and the customer's intention to revisit a robot-serviced restaurant.

In other words, for these emotional and relational factors, the expectation is that they enhance satisfaction, which then improves attitude, culminating in higher revisit intentions. This set of hypotheses (H4a through H4 d) contrasts with the functional factors (H1 series), where a direct attitude mediation was posited without involving satisfaction. The full set of hypothesised relationships is depicted in the proposed conceptual model (Fig. 1).

The moderating role of rapport

Customer–robot rapport refers to the sense of mutual understanding and connection that develops during their interaction. In service settings, rapport is known to amplify the effects of friendly behaviours on customer outcomes. Even for robots with limited social abilities, incorporating humanlike attributes (e.g. polite greetings, responsive gestures, a name or persona) can help establish rapport and enhance the hospitality experience (Kao & Huang, 2023; Kim et al., 2022a; Qiu et al., 2020). Prior studies have shown that robots exhibiting anthropomorphic features (like expressive motions, personalised responses or familiarity-building techniques) can increase perceived intimacy and service quality, thereby strengthening customers' emotional engagement (Oğan, 2024; Kim et al., 2022a, 2022b; Chiang & Trimi, 2020).

In essence, rapport functions as an 'interactional lubricant' that makes friendly robot behaviours feel more genuine and meaningful. Without rapport, a robot's polite or friendly

actions might seem mechanical and have limited emotional impact (Artstein et al., 2017). With strong rapport, those same actions are more likely to elicit positive emotions, as the customer perceives a warmer, more personal connection. Indeed, rapport can enable a form of emotional contagion in HRI: customers ‘catch’ the positive mood from the robot’s friendly demeanour (Stock & Merkle, 2018), further boosting their satisfaction (Wilson et al., 2017; Tian et al., 2021).

Rapport plays a complex role in shaping satisfaction and trust in HRI. Generally, higher rapport enhances satisfaction by making interactions more enjoyable and personable (Gremler & Gwinner, 2000; Nomura & Kanda, 2016). However, some evidence suggests that very high rapport might not always increase trust in robotic services. This is because customers ultimately expect service robots to be efficient and reliable; if a robot focuses too much on social bonding at the expense of task performance, highly rapport-rich interactions could paradoxically undermine perceptions of reliability (Tussyadiah et al., 2020; Lee et al., 2021).

Nonetheless, within moderate levels, rapport clearly strengthens the emotional bond, turning polite robotic behaviours into deeper engagement. Instruments like the Rapport Expectation with a Robot Scale (Nomura & Kanda, 2013, 2016) highlight how essential rapport is for

maximising the impact of a robot’s friendly behaviour on customer satisfaction. In this study, rapport is examined as a moderator of the effect of friendliness and trust on customer satisfaction. It is a relational perception that conditions other effects. That is, when rapport is high, the positive influence of a robot’s friendliness on satisfaction is expected to grow even stronger, as the customer feels a genuine social connection. Formally:

H5a. The positive relationship between perceived friendliness and customer satisfaction will grow stronger as customer-rapport increases.

Conversely, rapport may also interact with trust. Trust provides a functional assurance in the robot’s reliability (Roy et al., 2024), whereas rapport adds a relational layer on top of that trust. When both trust and rapport are present, customers perceive the robot to be not only competent but also socially engaging (Lee, 2024) (for example, a customer might initially trust a robot to deliver food on time, but if rapport is established, the customer might feel as if the robot genuinely ‘cares’ about their experience). High rapport thus transforms trust from a purely transactional belief (‘the robot will

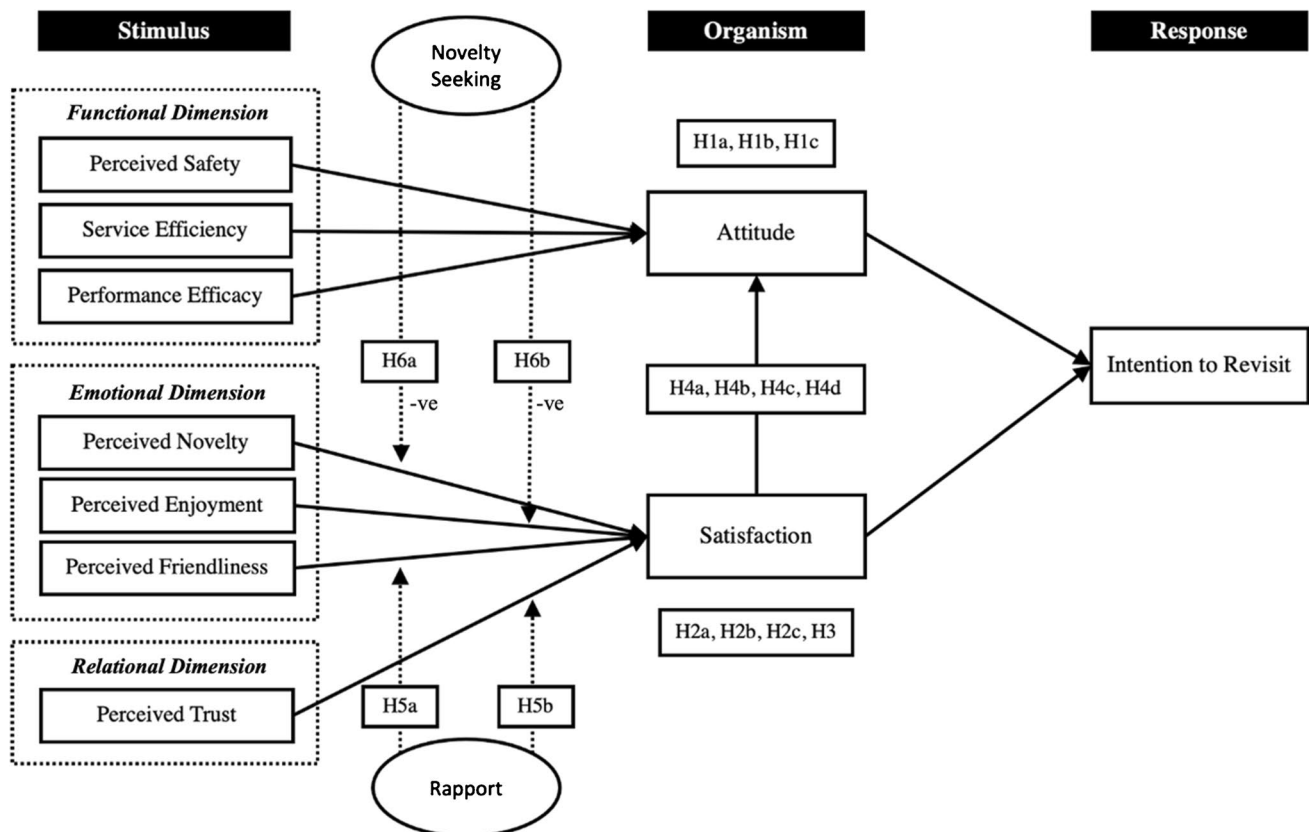


Fig. 1 Proposed conceptual model

do its job') into a more personal connection, which could further enhance satisfaction (Lee et al., 2021; Vargo & Lusch, 2004). There is reason to expect that trust's impact on satisfaction is magnified when rapport is strong, since the customer's confidence in the robot is reinforced by positive social interaction (Kim et al., 2022a, 2022b). Therefore:

H5b. The positive relationship between perceived trust and customer satisfaction will grow stronger as customer-rapport increases.

Together, H5a and H5b anticipate that rapport intensifies the beneficial effects of a robot's friendliness and reliability on how satisfied customers feel, by fostering intimacy and emotional resonance in the interaction.

The moderating role of novelty seeking

While perceived novelty generally has a positive effect on customer satisfaction in robotic service encounters (Ali et al., 2024; El-Said & Al Hajri, 2022; Sharma et al., 2023), the strength of this effect can vary widely across individuals (Assaker & Hallak, 2013). Customers differ in their inherent novelty-seeking tendencies—a personality trait describing one's desire for new, varied and unusual experiences. A high novelty-seeker actively pursues unique experiences and quickly grows accustomed to them, whereas a low novelty-seeker is more easily delighted by new experiences and retains that sense of novelty for longer. Prior work shows that novelty-seeking can moderate satisfaction derived from novel experiences: for some, novelty greatly enhances enjoyment, while for others (particularly those who constantly seek novelty) the boost is weaker or short-lived.

In a robotic restaurant, high novelty-seekers may initially be excited by the presence of robot servers, but their enthusiasm can fade relatively quickly. Because these individuals habitually seek novelty, each exposure reduces the 'freshness' of the experience—a phenomenon consistent with *diminishing marginal utility*, where repeated exposure to what was once novel yields declining enjoyment (Gocłowska et al., 2019; Alotaibi et al., 2024). Studies have found that people with strong novelty-seeking traits derive less satisfaction once an experience is no longer new, which aligns with observations that novelty-seeking dampens the long-term impact of novel features on satisfaction (Hirschman, 1980; El-Said & Al Hajri, 2022). Consequently, the positive relationship between perceived novelty of a robot service and customer satisfaction is expected to be weaker for high novelty-seekers, since they adapt quickly and crave newer stimuli (El-Said & Al Hajri, 2022; Assaker & Hallak, 2013).

By contrast, low novelty-seekers (who are not constantly chasing new experiences) tend to find the robot service highly novel and continue to appreciate its uniqueness for a longer period. For these customers, dining with robots represents a significant departure from routine; they do not habituate as quickly, allowing the novelty to have a stronger and more lasting positive effect on satisfaction (Ali et al., 2024).

Empirical evidence shows that for consumers low in novelty-seeking, the hedonic value of a novel service can meaningfully enhance delight and loyalty, whereas high novelty-seekers require ever-new innovations to maintain the same level of satisfaction (Ali et al., 2024). However, for high novelty-seekers, these values may lose their impact as their baseline expectation for unique experiences is higher, resulting in a weaker link between perceived novelty and satisfaction (El-Said & Al Hajri, 2022). Similar moderation effects have been observed in related contexts—for instance, in quick-service restaurants, high novelty-seeking customers showed lower engagement with robotic services if the novelty did not continually meet their elevated expectations (Alotaibi et al., 2024; Zemke et al., 2020).

Given this, novelty-seeking is proposed to moderate the effects of both novelty and enjoyment on satisfaction. First, for the novelty–satisfaction link:

H6a. The positive relationship between perceived novelty and customer satisfaction will be weaker when customer's novelty-seeking tendency is higher.

A parallel logic applies to perceived enjoyment. Enjoyment from the robot service, as noted, can stem partly from its novelty and fun factor (Sharma et al., 2023; Jain et al., 2023). Customers high in novelty-seeking may enjoy the robot interaction initially, but their enjoyment diminishes faster as the experience becomes familiar and they seek new forms of stimulation (El-Said & Al Hajri, 2022; Alotaibi et al., 2024). In fact, high novelty-seekers tend to discount or 'get used to' enjoyable features over time unless something new is introduced. On the other hand, low novelty-seekers, who value consistency and familiarity, can continue deriving satisfaction from the enjoyable aspects of a robot server without needing constant novelty (Ali et al., 2024). For them, the enjoyment from the interaction remains impactful over repeated visits, strengthening the enjoyment–satisfaction relationship. Therefore, it is hypothesised that:

H6b. The positive relationship between perceived enjoyment and customer satisfaction will be weaker when the customer's novelty-seeking tendency is higher.

Figure 1 illustrates the proposed conceptual model, encompassing all the hypothesised relationships (H1a–H6b).

Research method

Study context

A purposive sampling technique was employed to recruit participants with relevant and recent experience in robotic dining service environments. The target population included individuals aged 18 and above who had interacted with service robots in restaurants within the past year. This criterion ensured the collection of accurate and meaningful data reflecting real-world HRI experiences in structured dining contexts.

Participants were recruited primarily through social media platforms and online forums focused on dining and technology. Recruitment posts targeted urban areas such as Klang Valley, Johor Bahru and George Town, where robotic dining services are more prevalent. To ensure eligibility, participants completed an initial screening questionnaire, confirming their experience with robotic service interactions in the past year. Responses failing to meet these criteria were excluded from the final dataset.

The study included a diverse range of restaurant service robots performing core service functions such as food delivery and order facilitation (see Appendix 2). However, the study focused on non-humanoid robots, which are primarily task-oriented but may incorporate minimal anthropomorphic features such as screen-based facial expressions, interactive lighting and polite communication cues (Hlee et al., 2022; Shin, 2022). Unlike humanoid robots that rely on human-like gestures or speech, these robots prioritise functionality and efficiency while enhancing customer engagement through subtle social cues. This hybrid classification allowed the study to investigate how functional, emotional, and relational dimensions interact in non-humanoid robotic dining services.

Through this purposive sampling process, a total of 308 validated responses were obtained, ensuring sufficient data for strong analysis. Previous studies have relied on hypothetical or simulated interactions to assess customer attitudes toward service robots (Choi et al., 2019; Hu, 2021). These studies do not capture the complexities and dynamic of real-world interactions. By focusing on recent, first-hand experiences, this study minimised recall bias and provided insights grounded in actual customer-robot interactions. This approach supports the study's objective of understanding the interplay between functional, emotional, and relational dimensions of HRI in structured service settings.

Survey design and measurement

The questionnaire comprised seven sections including demographic, control variables and filter items. The first two sections provided a brief introduction to the study and the

researcher's background, followed by two filter questions. Section A gathered preliminary information about respondents' visits to restaurants using service robots, including the timing of their last visit, the frequency of visits, and their companions during the visit.

Survey items were adapted from established literature to suit the context of service robot restaurants. The functional dimension was assessed through perceived safety, service efficiency and performance efficacy. Perceived safety was measured using four items adapted from Barneck et al. (2009), while service efficiency was evaluated using four items from El-Said and Al Hajri (2022). Performance efficacy was also measured with four items adapted from Lu et al. (2019). The emotional dimension of HRI included constructs such as perceived friendliness, novelty and enjoyment. Perceived friendliness was assessed using four items from Hlee et al. (2022), while perceived novelty was measured with four items adapted from Li et al. (2021). Perceived enjoyment was assessed with five items based on Davis (1989) and Venkatesh (2000). Relational dimension, which are critical for trust and engagement in HRI, included constructs for perceived trust and rapport. Perceived trust was measured with four items adapted from Kim et al., (2022a, 2022b), while rapport was evaluated using three items from Gremler and Gwinner (2000).

To capture customer outcomes, customer satisfaction and attitude were measured alongside revisit intentions. Customer satisfaction was assessed with four items from Kim and Qu (2014), while customer attitude was measured using three items from Dabholkar and Bagozzi (2002). Revisit intentions were evaluated using four items adapted from Song et al., (2022a, 2022b). In addition to these primary constructs, two moderating variables were included in the study: novelty seeking and rapport. Novelty seeking was assessed using four items adapted from Dabholkar and Bagozzi (2002) to capture customers' tendency to seek out new and stimulating experiences. Rapport, as a moderating variable, reflected the quality of interaction between customers and robots and was measured using three items from Gremler and Gwinner (2000). All survey items were measured on a seven-point Likert scale, and full details of the survey items are provided in Appendix 1.

Sample and data collection

The required sample size was determined using G*Power 3.1, which recommended a minimum of 178 respondents to achieve 0.15 effect size, 0.05 significance level and 0.95 statistical power. To enhance reliability, 338 responses were collected. After excluding six ineligible responses and removing 24 statistical outliers (based on Mahalanobis

distance and extreme inconsistencies in responses), the final sample comprised 308 valid responses.

Data were analysed using partial least squares structural equation modelling (PLS-SEM) via SmartPLS 4.1.0.9 software. PLS-SEM was chosen due to the study's complex model, which incorporated 12 latent constructs and 50 observed indicators. This method effectively handles non-normal data distributions and allows for the simultaneous testing of direct and mediating relationships (Hair et al., 2014).

By integrating real-world customer experiences, non-humanoid robotic service interactions and structured theoretical models, this study advances the understanding of how functional efficiency, emotional engagement and relational trust shape customer satisfaction and behavioural intentions in robotic dining services.

Common method variance

To mitigate potential common method variance (CMV) from self-report surveys, a marker-based technique was applied prior to PLS-SEM analysis. A marker variable (MV) comprising three items from the 'attitude toward the colour blue' scale (Miller & Simmering, 2023) was included in the survey to detect CMV (Chin et al., 2013; Podsakoff et al., 2003, 2016; Tehseen et al., 2017). Comparing R^2 values for each endogenous construct, with and without the MV, showed negligible differences, confirming that CMV was not an issue (see Table 3).

Results and data analysis

The survey revealed a slight majority of female respondents (52.6%). Most participants were younger, with 71.4% aged 18–30. In terms of marital status, 73.1% were single, while 26.9% were married; among the married participants, 18.8% had children and 8.1% did not. Malaysian respondents constituted most of the sample (97.1%).

As for education, 63.3% held undergraduate degrees, 22.1% had advanced degrees (master's or doctoral) and 14.6% had secondary education or diploma qualifications. Occupationally, 43.2% were private sector employees, followed by students (25.3%), public sector employees (14.6%), self-employed individuals (10.7%), unemployed participants (2.9%) and 3.2% who did not disclose their employment status.

Engagement with robotic service restaurants Respondents reported diverse levels of engagement. Same-day visits accounted for 29.9%, while 4.2% visited the preceding day. Visits within the last week, month and 3 months were 14%, 21.1% and 24%, respectively. Most participants (66.2%) had

visited robotic service restaurants more than once, while 33.8% had only visited once. All visits occurred within the past year, ensuring the recency of experiences and reliability of the data.

Social dynamics of visits Dining with friends was the most common scenario, reported by 37.3% of respondents, followed by visits with family or relatives (29.9%). These results highlight the significant role of social contexts in shaping experiences in robotic dining environments.

Measurement model assessment

The measurement model was evaluated using a two-step approach. First, reliability and convergent validity were assessed by analysing average variance extracted (AVE) and composite reliability (CR). All values met the recommended thresholds (indicator loadings $\lambda > 0.5$, AVE > 0.5 , CR > 0.7), confirming strong reliability and validity (Hair et al., 2019, 2021) (see Table 4). Second, discriminant validity was tested using the heterotrait-monotrait (HTMT) ratio. Most HTMT values were below the 0.90 threshold (Table 5), except for rapport-perceived trust and satisfaction-attitude pairs. However, bootstrapped 90% bias-corrected and accelerated confidence intervals (10,000 subsamples) confirmed that the intervals did not straddle 0, establishing discriminant validity for all constructs (Franke & Sarstedt, 2019; Henseler et al., 2015).

Structural model

Before hypothesis testing, data distribution and model fit were evaluated to ensure the suitability of the analytical approach. Mardia's multivariate skewness ($\beta = 19.57927$, $p < 0.01$) and kurtosis ($\beta = 200.93643$, $p < 0.01$) tests indicated significant non-normality in the data (Cain et al., 2017). Consequently, partial least squares structural equation modelling (PLS-SEM) was employed, as it is robust to non-normal data distributions (Hair et al., 2021). This approach follows established methodological guidance for PLS-SEM application in marketing and information systems research. The path coefficients were estimated with 10,000 bootstrap

Table 3 CMV testing using marker variable

Endogenous variable	R^2 without MV	R^2 with MV	Difference
Attitude	0.578	0.578	0.000
Revisit Intention	0.610	0.611	– 0.001
Satisfaction	0.537	0.538	– 0.001

MV marker variable, CMV common method variance, R^2 coefficient of determination or variance explained

resamples, and both p values and 95% confidence intervals were used to assess significance, as recommended by recent statistical critiques (Becker et al., 2023; Hahn & Ang, 2017). Table 7 summarises the resulting path estimates and hypothesis tests. The structural model demonstrated satisfactory explanatory power. The R^2 values for the key endogenous constructs—Attitude (0.578), Satisfaction (0.537) and Revisit Intention (0.610)—all exceeded the 0.50 benchmark, indicating that the model explains a substantial portion of variance in these outcomes. These values meet Chin's (1998) criterion for adequate model fit in PLS models and suggest the included predictors are relevant (see Fig. 2 for the model overview). Collinearity diagnostics showed no issues: variance inflation factors (VIFs) ranged from 1.4 to 3.0, well below the conservative threshold of 3.3 (Diamantopoulos & Siguaw, 2006). Hence, multicollinearity is not a concern in interpreting the path coefficients. The model's predictive validity was also examined using the PLSpredict procedure with tenfold cross-validation (Shmueli et al., 2016). The results indicated strong out-of-sample predictive power (Table 6). For each manifest indicator of the key constructs, the root mean square error (RMSE) from the PLS-SEM predictions was lower than the RMSE from a naïve linear model (LM) benchmark, yielding positive predictive Q^2 values. In particular, the endogenous construct revisit intention showed a high Q^2_{predict} value of 0.464, reinforcing that the PLS model has robust predictive relevance for the intended outcomes. All PLS–LM difference values were negative, further confirming that the PLS model's predictions had less error than the linear alternative. These diagnostics indicate that the structural model is both strong in terms of explanatory and predictively strong and sound, providing a reliable basis for hypothesis testing.

Mediation result

The integration of the S–O–R and USUS frameworks offers a strong theoretical foundation for examining the mediating effects of in HRI. These findings highlight the influence of functional, emotional and relational dimensions, particularly in the context of non-humanoid robots operating in structured environments such as restaurants. Table 7 summarises the results of all tested hypotheses, illustrating the mediating roles of satisfaction and attitude across various relationships.

Furthermore, the framework incorporates moderators—such as rapport (RAP) and novelty-seeking tendencies (NOVS)—which influence the strength and direction of the mediated relationships. These moderating variables lead to the emergence of moderated mediation effects, where the indirect effects depend on the values of the moderators (Hayes, 2022). To evaluate these conditional processes, the index of moderated mediation (Preacher et al., 2007; Hayes, 2022) was employed.

Table 4 Assessment of measurement model on reliability, convergent validity and full collinearity

Construct	Items	λ	FC	CR (Rho-C)	AVE
Attitude	ATT1	0.813	2.788	0.877	0.641
	ATT2	0.762			
	ATT3	0.803			
	ATT4	0.823			
Novelty seeking	NOVSEE1	0.748	1.400	0.838	0.565
	NOVSEE2	0.806			
	NOVSEE5	0.737			
	NOVSEE6	0.712			
Performance efficacy	PEFF1	0.803	2.173	0.836	0.510
	PEFF2	0.737			
	PEFF3	0.832			
	PEFF4	0.557			
	PEFF5	0.602			
Perceived enjoyment	PENJ1	0.814	2.047	0.884	0.562
	PENJ2	0.761			
	PENJ3	0.802			
	PENJ4	0.675			
	PENJ5	0.719			
	PENJ6	0.717			
Perceived friendliness	PF1	0.822	2.052	0.873	0.632
	PF2	0.804			
	PF3	0.782			
	PF4	0.771			
Perceived novelty	PN1	0.693	1.749	0.838	0.566
	PN2	0.785			
	PN3	0.824			
	PN4	0.697			
Perceived safety	PSAF1	0.779	1.676	0.857	0.600
	PSAF2	0.747			
	PSAF3	0.754			
	PSAF4	0.818			
Perceived trust	PT1	0.825	3.040	0.836	0.563
	PT2	0.793			
	PT3	0.608			
	PT4	0.757			
Rapport	RAPP1	0.773	2.757	0.862	0.610
	RAPP2	0.838			
	RAPP3	0.817			
	RAPP4	0.687			
Revisit intention	RV11	0.783	2.574	0.881	0.650
	RV12	0.827			
	RV13	0.802			
	RV14	0.813			
Satisfaction	SAS1	0.827	2.949	0.883	0.654
	SAS2	0.790			
	SAS3	0.792			
	SAS4	0.824			
Service efficiency	SEFF1	0.796	1.794	0.893	0.676
	SEFF2	0.795			
	SEFF3	0.848			
	SEFF4	0.849			

λ loading, CR composite reliability, AVE average variance extracted, FC variance inflation factor from full collinearity testing

Table 5 Measurement model-discriminant validity via HTMT ratio

	ATT	NOVS	ENJ	SAF	TRU	FRI	NOVL	EFFC	RAP	RVI	SEFF
1. ATT											
2. NOVS	0.540										
3. ENJ	0.345	0.153									
4. SAF	0.348	0.129	0.563								
5. TRU	0.484	0.133	0.554	0.657							
6. FRI	0.659	0.393	0.537	0.398	0.265						
7. NOVL	0.546	0.395	0.512	0.231	0.217	0.675					
8. EFFC	0.341	0.097	0.499	0.713	0.888	0.204	0.179				
9. RAP	0.493	0.211	0.721	0.623	0.903	0.395	0.328	0.653			
10. RVI	0.812	0.558	0.389	0.389	0.552	0.484	0.614	0.449	0.522		
11. SAT	0.903	0.558	0.364	0.341	0.489	0.664	0.601	0.313	0.462	0.828	
12. SEFF	0.602	0.272	0.547	0.402	0.387	0.588	0.479	0.490	0.494	0.574	0.591

ATT attitude, NOVS novelty seeking, ENJ perceived enjoyment, SAF perceived safety, TRU perceived trust, FRI perceived friendliness, NOVL perceived novelty, EFFC performance efficacy, RAP rapport, RVI revisit intention, SAT satisfaction, SEFF service efficiency

Mediating effects of attitude

For H1a, which hypothesised that perceived safety (SAF) positively influences RVI through attitude (ATT), the results revealed no significant direct or indirect effects ($\beta = 0.014$, $p = 0.209$). This indicates that SAF does not impact revisit intentions through ATT, rendering the hypothesis not supported. This suggests that safety, while a critical functional factor, may not influence attitudes strongly enough to shape behavioural outcomes in non-humanoid robotic interactions.

In contrast, H1b, which examined the effect of service efficiency (SEFF) on RVI through ATT, revealed significant direct ($\beta = 0.081$, $p = 0.002$) and indirect ($\beta = 0.049$, $p = 0.002$) effects, supporting complementary mediation. This confirms that SEFF enhances customer attitudes, which, in turn, positively influences revisit intentions. The results stress the importance of efficiency as a functional stimulus within the S–O–R framework in structured hospitality environments.

For H1c, testing performance efficacy (EFFC) as a predictor of ATT and RVI, a significant direct effect was found ($\beta = 0.124$, $p = 0.019$), but no mediation effect was observed. The mediation type is classified as direct-only (DO), which does not align with the hypothesised mediation. Thus, H1c was not supported, suggesting that EFFC directly influences revisit intentions without necessarily shaping customer attitudes.

Mediating effects of satisfaction

The mediating role of satisfaction (SAS) connects experiential and relational dimensions with behavioural outcomes,

illustrating the interplay of novelty, enjoyment and trust within the S–O–R and USUS frameworks.

For H2a, perceived novelty (NOVL) was hypothesised to positively influence RVI through SAS. The findings revealed significant direct and indirect effects ($\beta = 0.067$, $p = 0.002$), supporting complementary mediation. This demonstrates that the novelty of non-humanoid robots enhances satisfaction, which translates into higher revisit intentions, reflecting the dual experiential and functional value of novelty.

In H2b, perceived enjoyment (ENJ) was expected to enhance SAT which in turn boosts RVI. However, the results showed a *significant negative indirect effect* ($\beta = -0.035$, $p = 0.052$) of ENJ on RVI via SAT and no significant direct effect. The negative direction of the mediation highlights a potential disconnect between ENJ and satisfaction in robotic interactions, rendering the hypothesis not supported. In other words, excessive focus on enjoyment undermined satisfaction, leading to lower revisit intentions than expected.

For H2c, perceived friendliness (FRI) was tested as a predictor of SAS and RVI. While a significant indirect effect was found ($\beta = 0.105$, $p < 0.001$), the direct effect was negative ($\beta = -0.124$, $p = 0.028$), resulting in competitive mediation. This suggests that while FRI positively impacts satisfaction, it negatively influences revisit intentions directly, leading to the hypothesis being not supported. This hypothesis assumes perceived friendliness increases satisfaction, driving revisit intention. While friendliness did raise satisfaction, there was a negative direct effect on revisit intention, creating a competitive mediation (positive via satisfaction, negative direct). Thus, an overly friendly robot can backfire on loyalty, as high friendliness conflicted with customers' revisit intentions.

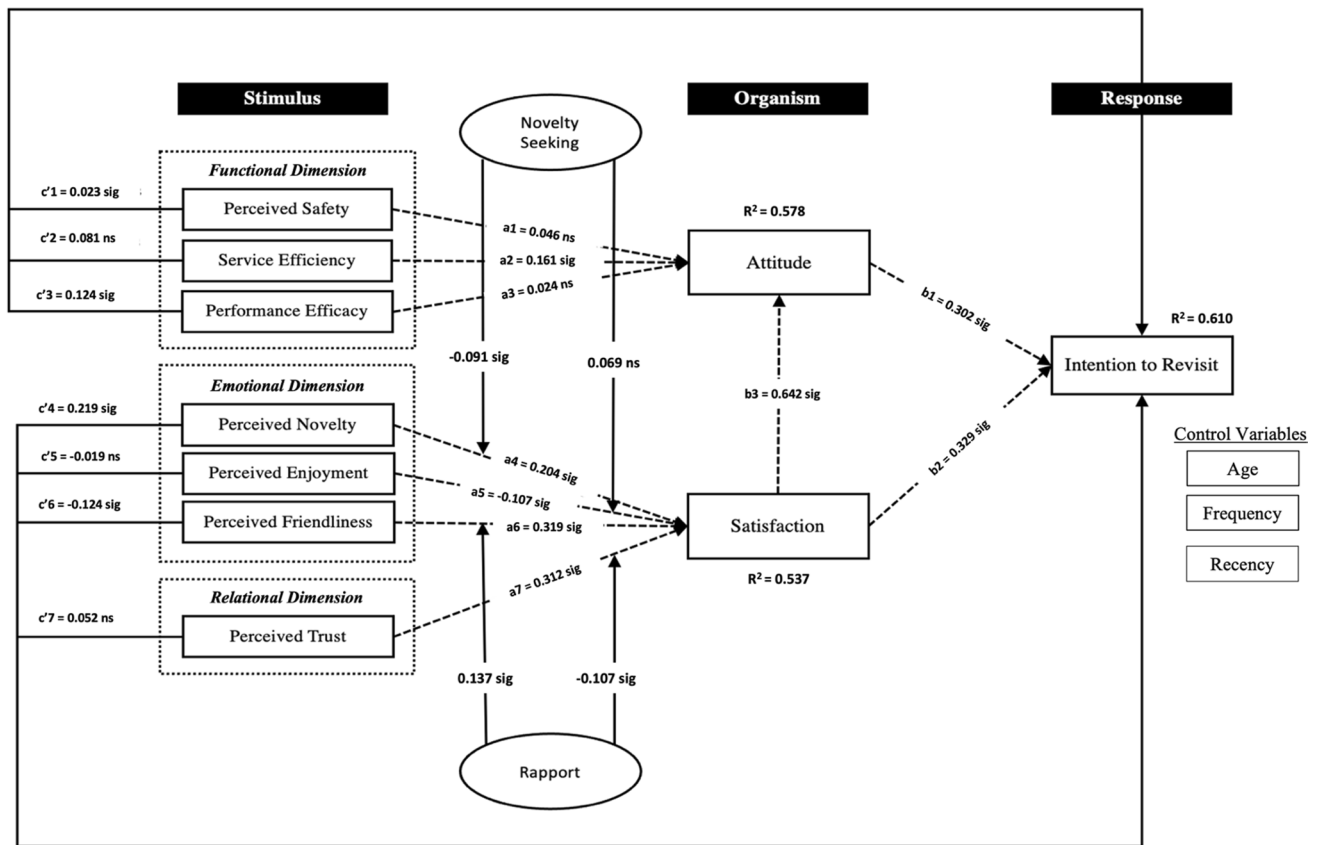


Fig. 2 Structural equation modelling analysis

Table 6 $PLS_{Predict}$ for the model

MV	$Q^2_{predict}$	RMSE			Decision
		PLS	LM	PLS-LM	
RVI1	0.291	0.747	0.819	-0.072	Strong predictive power
RVI2	0.261	0.979	1.070	-0.091	
RVI3	0.297	1.163	1.198	-0.035	
RVI4	0.348	0.908	0.978	-0.070	

RVI revisit intention, LM linear model, RMSE root mean square error

Lastly, H3 posited that perceived trust (TRU) influences RVI through SAS. The results supported indirect-only (IO) mediation ($\beta = 0.102$, $p < 0.001$), aligning with the hypothesis. This confirms that trust plays a pivotal role in enhancing satisfaction, which in turn fosters revisit intentions in robot-served restaurant environments.

Serial mediation via satisfaction and attitude

Serial mediation effects were analysed to capture the combined influence of SAS and attitude (ATT). For H4a, the results revealed a significant serial mediation effect ($\beta = 0.039$, $p = 0.001$), supporting the hypothesis that NOVL impacts RVI through SAS and ATT.

This shows the importance of novelty in driving both emotional satisfaction and attitudinal changes.

H4b extends H2b in a serial path. ENJ was hypothesised to influence RVI via SAS and ATT. While the serial mediation effect was significant ($\beta = -0.021$, $p = 0.042$), its negative direction contradicts the hypothesis, leading to it being not supported. Similarly, for H4c, FRI was found to exhibit a positive serial mediation effect ($\beta = 0.062$, $p < 0.001$) but a negative direct effect, resulting in competitive mediation. This inconsistency rendered H4c not supported. Conversely, H4d, which tested TRU, showed a significant serial mediation effect ($\beta = 0.060$, $p < 0.001$), supporting the hypothesis that trust influences RVI through satisfaction and attitude.

Moderating result

Moderating effects of rapport and novelty-seeking

The moderating effects were tested to assess their influence on the relationships between stimuli and organismic responses. For H5a, the findings showed that rapport (RAP) significantly strengthened the positive relationship between FRI and SAS ($\beta = 0.137$, $p = 0.003$), supporting the hypothesis (illustrated in Fig. 3). This indicates that rapport

Table 7 Results

Mediators	Hyp	Path	Parameters	β	Std. Dev	<i>t</i> value	<i>p</i> value	PCI LL	PCI UL	Supp?	MT
ATT	H _{1a}	a ₁ b ₁	SAF→ATT→RVI	0.014	0.017	0.809	0.209	−0.012	0.045	No	DO
	H _{1b}	a ₂ b ₁	SEFF→ATT→RVI	0.049	0.017	2.896	0.002	0.025	0.081	Yes	CM
	H _{1c}	a ₃ b ₁	EFFC→ATT→RVI	0.007	0.016	0.467	0.320	−0.019	0.032	No	DO
SAS	H _{2a}	a ₄ b ₂	NOVL→SAS→RVI	0.067	0.023	2.956	0.002	0.035	0.110	Yes	CM
	H _{2b}	a ₅ b ₂	ENJ→SAS→RVI	−0.035	0.022	1.628	0.052	−0.080	−0.007	No	CM
	H _{2c}	a ₆ b ₂	FRI→SAS→RVI	0.105	0.029	3.648	< 0.001	0.064	0.161	No	CP
	H ₃	a ₇ b ₂	TRU→SAS→RVI	0.102	0.030	3.376	< 0.001	0.061	0.165	Yes	IO
Serial SAS & ATT	H _{4a}	a ₄ b ₃ b ₁	NOVL→SAS→ATT→RVI	0.039	0.013	3.046	0.001	0.021	0.065	Yes	CM
	H _{4b}	a ₅ b ₃ b ₁	ENJ→SAS→ATT→RVI	−0.021	0.012	1.723	0.042	−0.046	−0.005	No	IO
	H _{4c}	a ₆ b ₃ b ₁	FRI→SAS→ATT→RVI	0.062	0.016	3.887	< 0.001	0.040	0.095	No	CP
	H _{4d}	a ₇ b ₃ b ₁	TRU→SAS→ATT→RVI	0.060	0.018	3.310	< 0.001	0.036	0.099	Yes	IO
Direct effect		c' ₁	SAF→RVI	0.023	0.054	0.419	0.338	−0.070	0.109	ns	
		c' ₂	SEFF→RVI	0.081	0.049	1.656	0.049	0.002	0.163	sig	
		c' ₃	EFFC→RVI	0.124	0.060	2.065	0.019	0.023	0.221	sig	
		c' ₄	NOVL→RVI	0.219	0.052	4.242	< 0.001	0.132	0.303	sig	
		c' ₅	ENJ→RVI	−0.019	0.054	0.347	0.364	−0.113	0.066	ns	
		c' ₆	FRI→RVI	−0.124	0.065	1.907	0.028	−0.233	−0.018	sig	
		c' ₇	TRU→RVI	0.052	0.063	0.824	0.205	−0.048	0.159	ns	
Moderation	H _{5a}		RAP*FRI→SAS	0.137	0.050	2.713	0.003	0.054	0.220	Yes	
	H _{5b}		RAP*TRU→SAS	−0.107	0.041	2.628	0.004	−0.169	−0.035	No	
	H _{6a}		NOVS*NOVL→SAS	−0.091	0.046	1.977	0.024	−0.166	−0.016	Yes	
	H _{6b}		NOVS*ENJ→SAS	0.069	0.053	1.308	0.095	−0.025	0.149	No	
Control variables:			Age→RVI	0.095	0.031	3.034	0.001	0.044	0.147	sig	
			Frequency→RVI	0.061	0.040	1.509	0.066	−0.007	0.127	ns	
			Recency→RVI	0.043	0.039	1.086	0.139	−0.020	0.109	ns	

Mediation types (MT): *DO* direct only, *CM* complementary mediation (Both direct and indirect effects are significant and align in direction), *IO* indirect only (Only the indirect path is significant), *CP* competitive (Direct and indirect effects are significant but have opposing signs), *NM* no mediation (Neither direct nor indirect path is significant). Variables: *SAF* perceived safety, *SEFF* service efficiency, *EFFC* performance efficacy, *NOVL* perceived novelty of robot, *ENJ* perceived enjoyment, *FRI* perceived friendliness, *TRU* perceived trust, *ATT* attitude, *SAS* satisfaction, *RVI* revisit intention, *RAP* robot rapport, *NOVS* novelty seeking tendency of restaurant customer

Sig. significant, *ns* not significant, β standardised beta, *Supp?* supported or not

amplifies the emotional connection between friendliness and satisfaction, enhancing relational dynamics.

However, for H5b, which hypothesised a positive moderation effect of RAP on the TRU-SAS relationship, the results revealed a significant but negative moderation ($\beta = -0.107$, $p = 0.004$). This contradiction suggests that higher rapport might shift the focus away from functional trust, emphasising emotional aspects instead (See Fig. 5). As a result, the hypothesis was not supported.

For novelty-seeking, H6a proposed that novelty-seeking tendencies (NOVS) weaken the positive relationship between NOVL and SAS. The findings supported this hypothesis, as the moderation effect was significant and negative ($\beta = -0.091$, $p = 0.024$), indicating that high novelty-seekers derive less satisfaction from novelty (see Fig. 4). In contrast, H6b, which posited that NOVS moderates the ENJ-SAS relationship, showed no significant moderation effect ($\beta = 0.069$,

$p = 0.095$). This rendered H6b not supported (see Figs. 3, 4 and 5).

Conditional mediation insights

Table 8 highlights conditional mediation effects under different levels of moderators (Preacher et al., 2007; Spiller et al., 2013). Although not hypothesised a priori, these analyses were conducted post hoc to examine potential boundary conditions of the observed mediation effects. This approach enabled the testing of conditional mechanisms, that is, whether the mediation effects hold across different levels of the moderating variables that were found to be significant in Table 7.

For $TRU \rightarrow SAS \rightarrow ATT \rightarrow RVI$, the effect strengthened as RAP increased, with the effect size at +1 SD ($\beta = 0.044$, $p = 0.014$) being weaker than at −1 SD ($\beta = 0.085$, $p = 0.000$). This suggests that higher RAP negatively impacts

TRU's influence on RVI. This indicates that the mediated effect of trust on revisit intention is amplified when rapport is low. For $FRI \rightarrow SAS \rightarrow ATT \rightarrow RVI$, the indirect effect was stronger at +1 SD RAP ($\beta = 0.090, p = 0.000$) than at -1 SD ($\beta = 0.044, p = 0.005$), supporting the positive moderating role of RAP on FRI. These results indicate that the mediated effect of friendliness is more pronounced at high levels of rapport, with diminishing effects as rapport decreases.

For $NOVL \rightarrow SAS \rightarrow ATT \rightarrow RVI$, novelty-seeking (NOVS) demonstrated significant conditional effects. At high levels of NOVS (+1 SD), the mediation effect was weaker ($\beta = 0.022, p = 0.079$) compared to lower NOVS (-1 SD, $\beta = 0.066, p = 0.000$). This aligns with H6a, as high novelty-seekers derive less satisfaction from novelty over time. This suggest that the mediated effect of novelty on revisit intention strengthens as novelty-seeking tendencies decrease, supporting the presence of moderated mediation.

However, for H6b, NOVS did not significantly moderate the relationship between ENJ and SAS, as shown by insignificant effects across conditions.

Discussion

This study provides critical insights into HRI within the structured service context of robot-served restaurants. The findings, summarised in Table 9, offer both theoretical and practical implications, revealing the complex relationship between functional, emotional, and relational dimensions of HRI in shaping customer satisfaction and revisit intention. While many results align with established frameworks like the S-O-R and USUS frameworks, others challenge existing assumptions and highlight areas for further exploration.

Fig. 3 Simple slope between FRI and SAS at different levels of RAP

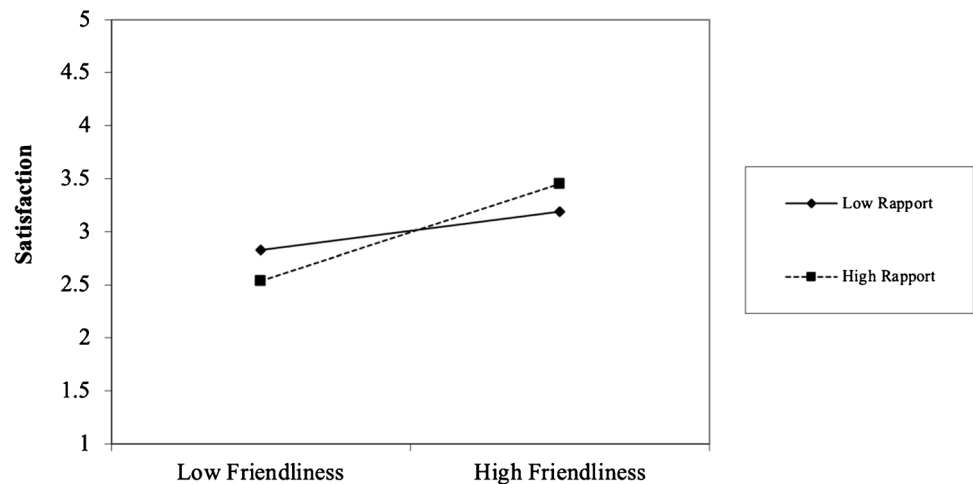


Fig. 4 Simple slope between NOVL and SAS at different levels of NOVS

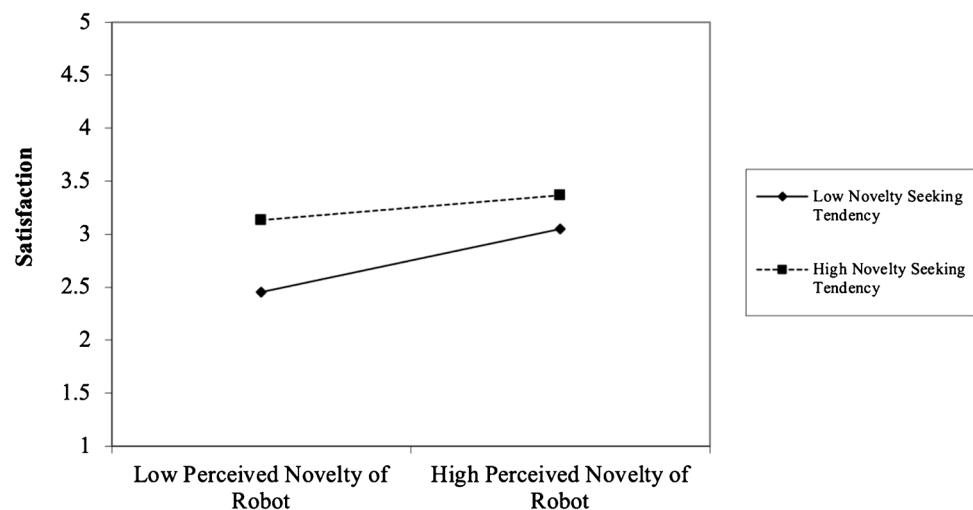
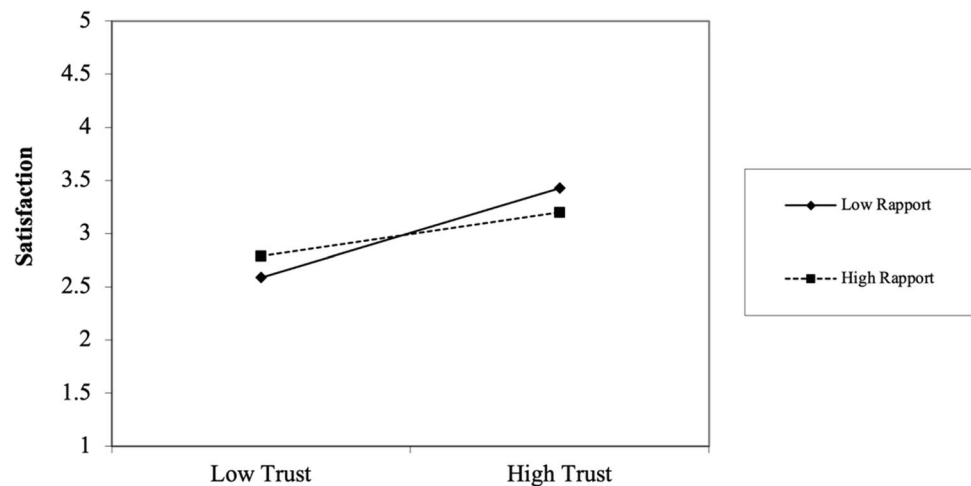


Fig. 5 Simple slope between TRU and SAS at different level of RAP



Functional service factors and revisit intention

The results for the H1 hypotheses highlight a complex role of functional service qualities in shaping customer loyalty. Perceived safety (H1a) showed no significant effect on revisit intention via attitude. In practical terms, this suggests that basic safety is taken as a given. Customers seem to assume the robot is safe and instead prioritise other factors. In contrast, service efficiency (H1b) emerged as a critical driver: it had a significant complementary mediation effect, meaning it boosts revisit intention by first improving customer attitude. When a service robot operates swiftly and reliably (e.g. delivering food promptly in a restaurant), it leaves a favourable impression that translates into increased intent to return. Performance efficacy (H1c), the robot's competent task performance, influenced revisit intention through a direct-only effect. This indicates that customers value a robot that can effectively perform its job, and this appreciation directly encourages repeat patronage without necessarily altering their interim attitude toward the robot. Theoretically,

these findings imply that within the S–O–R framework, not all functional stimuli feed into the ‘organism’ (attitude) equally. Service efficiency functions as a stimulus that does elevate internal evaluations (attitudes) and thus behaviour, whereas performance efficacy exerts its impact in a more outcome-driven manner (customers return because the service outcome was good, even if their attitude toward the robot itself is not strongly changed). Meanwhile, the lack of any effect for safety shows that some functional attributes might be mere ‘hygiene’ factors, which are necessary but not sufficient to sway customer attitudes or retention.

The role of enjoyment and friendliness in HRI

The counterintuitive effects of *enjoyment* and *friendliness* in our findings suggest that more of these seemingly positive factors do not always equate to greater customer retention. Notably, H2b/H4b showed that *enjoyment* exerted a significant negative indirect effect on revisit intention (via satisfaction, and serially through satisfaction → attitude)

Table 8 Moderated mediation

Moderator	Conditional Mediation	β	Std Dev	t-value	p-value	PCI-LL	PCI-UL
RAP	TRU → SAS → ATT → RVI conditional on RAP at +1 SD	0.044	0.020	2.185	0.014	0.017	0.084
	TRU → SAS → ATT → RVI conditional on RAP at Mean	0.065	0.019	3.333	< 0.001	0.039	0.104
	TRU → SAS → ATT → RVI conditional on RAP at −1 SD	0.085	0.024	3.541	< 0.001	0.051	0.132
RAP	FRI → SAS → ATT → RVI conditional on RAP at +1 SD	0.090	0.024	3.737	< 0.001	0.056	0.139
	FRI → SAS → ATT → RVI conditional on RAP at Mean	0.067	0.018	3.809	< 0.001	0.042	0.102
	FRI → SAS → ATT → RVI conditional on RAP at −1 SD	0.044	0.017	2.559	0.005	0.020	0.078
NOVS	NOVL → SAS → ATT → RVI conditional on NOVS at +1 SD	0.022	0.016	1.411	0.079	−0.002	0.050
	NOVL → SAS → ATT → RVI conditional on NOVS at Mean	0.044	0.014	3.115	0.001	0.024	0.072
	NOVL → SAS → ATT → RVI conditional on NOVS at −1 SD	0.066	0.020	3.336	< 0.001	0.039	0.106

NOVL perceived novelty, FRI perceived friendliness, TRU perceived trust, ATT attitude, SAS satisfaction, RVI revisit intention, RAP rapport, NOVS novelty seeking tendencies of restaurant customer

(see Table 9). This runs contrary to typical expectations that a fun or pleasurable robot interaction enhances satisfaction and repeat patronage (El-Said & Al Hajri, 2022). One explanation is that in a task-oriented dining context (e.g. robotic food delivery), an overly entertaining robot can be perceived as a novelty gimmick that distracts from core service quality. Drawing on expectancy-disconfirmation theory (Oliver, 1980), customers in structured environments anticipate functional attributes, such as reliability and operational efficiency, over hedonic or relational features. Customers might enjoy the interaction in the moment but view it as a one-off experience, satisfying curiosity rather than building loyalty. In fact, highly novel, anthropomorphic experiences can stimulate variety-seeking behaviour, prompting patrons to try something new next time rather than return (Liu et al., 2025). Thus, consistent with recent cautions in the literature (Oğan, 2024; Pitardi et al., 2024), our results highlight an enjoyment paradox: enjoyment alone may not translate into enduring commitment when it is not aligned with customers' primary service goals.

Turning to *friendliness*, H2c/H4c revealed a competitive mediation: the robot's friendliness had a positive indirect effect on revisit intention via increased satisfaction, yet a *negative direct effect*. In other words, a friendly demeanour made people feel satisfied, but at the same time, some aspect of that friendliness discouraged their return. In plain terms, while a friendly robot made customers more satisfied, something about that friendliness also discouraged customers from returning (the net total effect was not positive). A possible theoretical reason is that while social robots can mimic surface-level warmth, they still lack genuine human empathy and personalisation in service encounters (Wirtz et al., 2025). This dynamic is supported by role congruity theory (Eagly & Karau, 2002). The friendly robot might have improved the immediate experience (e.g. novelty, polite service), but it could not foster the authentic social connection or trust that underpins loyalty (El-Said & Al Hajri, 2022). Indeed, over-anthropomorphism or 'too much' friendliness can cross into uncanny or insincere territory, leading to discomfort or a sense that the experience is gimmicky (Li et al., 2023). Service context is critical here: diners expecting efficient, seamless service may react negatively if a robot's social behaviour feels out of place. For instance, introducing social robots in culturally themed restaurants offers novel interactions but can also undermine the perceived authenticity of the experience (Huo et al., 2025). This context mismatch might explain the direct negative impact of friendliness on revisit intentions; patrons enjoyed the robot's courtesy, yet subconsciously missed the human touch or felt the concept did not fit the dining atmosphere. From a social exchange theory perspective (Homans 1958; Blau 1964), one could say the robot's friendliness provided relational value (a pleasant interaction), but perhaps customers

felt the exchange lacked relational depth. A genuine relational exchange in services often involves empathy, personal attention and trust, facets that a robot cannot fully deliver. A similar pattern is observed in religious consumer contexts. For example, Al-Hajla et al. (2019) found that Islamic brand personality, a symbolic construct, did not significantly influence adoption behaviour among Muslim consumers unless it was reinforced by more utilitarian criteria such as relative advantage and perceived compatibility. In both cases, symbolic cues alone were insufficient to drive behavioural outcomes when they failed to align with consumers' core expectations of functionality and appropriateness for the service context. Therefore, the incremental benefit of robot friendliness can plateau quickly. Our findings urge a reconsideration of the common assumption that simply making service robots more 'likable' (through enjoyment or friendliness) will automatically boost customer retention.

In the context of human–robot dining interactions, the findings for H6a and H6b reveal how customers' novelty-seeking traits shape satisfaction outcomes. H6a predicted that the positive effect of perceived novelty on satisfaction would be weaker for high novelty-seekers. This hypothesis was supported, indicating a significant negative moderation effect: high novelty-seeking individuals derive comparatively less satisfaction from robotic novelty. The result aligns with hedonic adaptation theory, which posits that repeated exposure to novel stimuli yields diminishing enjoyment over time. High novelty-seekers quickly habituate to the robot's novelty, consistent with diminishing marginal utility (Gocłowska et al., 2019; Alotaibi et al., 2024). Moreover, expectancy-disconfirmation theory (Oliver, 1980) provides a complementary lens: novelty-seekers' elevated expectations for unique experiences mean robotic services often merely meet rather than exceed their novelty threshold, limiting satisfaction gains (El-Said & Al Hajri, 2022). In contrast, H6b posited a similar moderation for perceived enjoyment's effect on satisfaction, but this was not supported. The impact of enjoyment remained stable across novelty-seeking levels, suggesting that the enjoyment derived from engaging with a robot server is less contingent on one's novelty appetite. Figure 4 illustrates this interaction: the novelty–satisfaction slope is steep under low novelty-seeking but flattens at high novelty-seeking levels. Table 8 further confirms this pattern via a moderated mediation analysis: at high novelty-seeking (+ 1 SD), the indirect effect of novelty on revisit intentions via satisfaction (and attitude) is substantially attenuated ($\beta \approx 0.02$, n.s.), whereas at low novelty-seeking (− 1 SD) it remains significant and stronger ($\beta \approx 0.07$, $p < 0.001$). This conditional process result (Preacher et al., 2007) indicates that novelty-driven satisfaction translates into repeat patronage primarily for customers with lower novelty-seeking dispositions. A plausible reason is that by now robotic service is becoming mainstream enough that

Table 9 Summary of key findings and hypothesis results in human–robot interaction

Hypothesis	Relationship	Key Finding	Explanation/Impact
H1a	SAF → ATT → RVI	No significant direct or indirect effects (Not supported)	Safety does not influence revisit intention via attitude, suggesting that customers prioritise other functional or relational dimensions over perceived safety
H1b	SEFF → ATT → RVI	Complementary mediation (Supported)	Service efficiency drives revisit intention through attitude, highlighting its critical role in structured environments
H1c	EFFC → ATT → RVI	Direct-only effect (Not supported)	Performance efficacy directly influences revisit intention but does not mediate through attitude, suggesting its standalone importance in customer evaluations
H2a	NOVL → SAS → RVI	Complementary mediation (Supported)	Novelty positively influences satisfaction and revisit intention, reinforcing its role as an experiential driver in customer loyalty
H2b	ENJ → SAS → RVI	Negative indirect effect (Not supported)	Misaligned enjoyment behaviours reduce satisfaction, possibly due to perceptions of inauthenticity or overemphasis on hedonic value
H2c	FRI → SAS → RVI	Competitive mediation (Not supported)	While friendliness positively influences satisfaction, its negative direct effect on revisit intention suggests conflicting customer priorities between emotional engagement and functional reliability
H3	TRU → SAS → RVI	Indirect-only mediation (Supported)	Trust positively influences revisit intention entirely through satisfaction, confirming its importance in relational dynamics
H4a	NOVL → SAS → ATT → RVI	Positive serial mediation (Supported)	Novelty enhances revisit intention through combined effects on satisfaction and attitude, demonstrating its broad impact on customer experience
H4b	ENJ → SAS → ATT → RVI	Negative serial mediation (Not supported)	Enjoyment negatively affects revisit intention through satisfaction and attitude, showing potential over-familiarity or misaligned behaviours
H4c	FRI → SAS → ATT → RVI	Competitive serial mediation (Not supported)	Friendliness exhibits conflicting direct and mediated effects, indicating the need for balanced design between relational and functional features
H4 d	TRU → SAS → ATT → RVI	Positive serial mediation (Supported)	Trust significantly influences revisit intention via satisfaction and attitude, highlighting its central role in relational engagement
H5a	RAP * FRI → SAS	Positive moderation (Supported)	Rapport amplifies the positive relationship between friendliness and satisfaction, demonstrating the complementary role of relational dynamics
H5b	RAP * TRU → SAS	Negative moderation (Not supported)	Excessive rapport weakens trust's influence on satisfaction, potentially due to perceptions of over-familiarity or diminished professionalism
H6a	NOVS * NOVL → SAS	Negative moderation (Supported)	High novelty-seekers experience weaker relationships between novelty and satisfaction, consistent with adaptation-level theory
H6b	NOVS * ENJ → SAS	No significant moderation (Not supported)	Enjoyment's effect on satisfaction remains stable across different levels of novelty-seeking, suggesting that enjoyment operates independently of novelty-seeking tendencies
Conditional Mediation	Multiple paths	Moderators alter indirect effects in key relationships	Rapport strengthens FRI's effects but weakens TRU's impact. High NOVS reduces NOVL's mediated effects, while low NOVS supports lasting satisfaction from novelty

even low novelty-seekers are reasonably receptive to it, levelling the field. It is also possible that diners self-selecting into a robot-serviced restaurant had a minimum affinity for

novelty, reducing variance. In short, the impact of enjoyment on satisfaction appeared uniform across customer types in our sample. This non-finding is itself instructive. It suggests

that *novelty effects* may be less about stable ‘seeking’ traits and more about situational factors. As the novelty of robots wears off in everyday settings, simple enjoyment might not distinguish between customer segments as much as anticipated (cf. Pitardi et al., 2024).

A complex interplay of rapport and trust

Relational dimensions in HRI, particularly customer–robot rapport and trust, showed an intriguing moderated relationship. In general, trust in the service robot proved critical for satisfaction and loyalty, i.e. perceived trustworthiness of the robot had a strong positive impact on satisfaction, which in turn drove revisit intention (H3 supported via indirect-only mediation). This underscores that customers need to trust the robot’s ability and reliability to feel satisfied and committed. Trust’s influence also carried through in the serial mediation via attitude (H4 d: trust → satisfaction → attitude → revisit, supported), indicating that trust builds favourable attitudes as well. This aligns with a fundamental tenet of social exchange and relationship marketing: trust is the foundation of loyalty, even in technologically-mediated interactions (Morgan & Hunt 1994; Kim et al., 2021). However, our moderated findings qualify this by showing that the importance of trust can be altered by the level of rapport a customer feels with the robot.

The findings reveal a complex role of customer–robot rapport in shaping satisfaction. As hypothesised in H5a, rapport significantly *amplified* the effect of perceived robot friendliness on customer satisfaction. This aligns with prior service literature showing that warm, friendly interactions foster rapport, which in turn elevates customer satisfaction (Borghi et al., 2023). As illustrated in Fig. 3, when customers felt a strong sense of rapport with the robot, even slight increases in the robot’s friendliness led to big jumps in satisfaction. Rapport represents a personal connection marked by enjoyable, friendly engagement (Gremler & Gwinner, 2000). When such a bond is present, friendly behaviours from the robot are more deeply appreciated and impactful, leading to higher satisfaction. In essence, rapport creates an emotional buffer that magnifies positive stimuli, i.e. a friendly robot seems *even friendlier* and more satisfying when the customer feels a social connection with it. This result reinforces Gremler and Gwinner’s (2000) classic insight that greater rapport yields greater satisfaction in service exchanges. It also fits with recent robot studies finding that encouraging human–robot rapport (e.g. via conversational warmth) boosts customers’ overall experience (Borghi et al., 2023).

Surprisingly, however, H5b revealed that *high rapport actually weakened the positive influence of trust on satisfaction*. Figure 5 illustrates this paradox: at low levels of rapport, increases in trust strongly boost satisfaction, but at high

rapport, the trust–satisfaction slope flattens (the service is already satisfying due to rapport, so additional trust yields diminishing returns). In other words, when customers felt a strong personal rapport with the service robot, the usual importance of trust, defined as belief in the robot’s ability to deliver on needs (Sharma et al., 2023), was partially diluted. Several theoretical explanations can be advanced for this unexpected moderation. One possibility is a *redundancy effect*: rapport and trust both contribute to a sense of security and comfort, so a high level of rapport may have already fulfilled much of the customer’s psychological need, leaving less incremental benefit for trust. The customer, feeling emotionally satisfied by the friendly bond, may not derive as much additional satisfaction from cognitive assurances of the robot’s reliability. Another, related explanation is *shifting focus or role ambiguity*. A highly personable robot could blur the line between ‘service tool’ and ‘social partner’. When the robot is treated more like a companion, customers might place greater weight on relational warmth and less on task-based reliability in evaluating their experience. This aligns with social cognition research suggesting a warmth–competence trade-off: extremely friendly (high-rapport) agents might inadvertently be seen as less task-competent (Schömbbs et al., 2023). In this study’s context, strong rapport may have overshadowed competence cues, thereby muting the impact of trust on satisfaction. Additionally, an overly social robot could induce a mild *social overload* where some patrons might feel overwhelmed or unsure how to reciprocate, which could further dampen the influence of trust. Taken together, these interpretations suggest that rapport can at times substitute for, rather than supplement, the role of trust in driving satisfaction.

These findings show that rapport is fundamentally a perceived relational bond in the interaction. Accordingly, this study has modelled rapport as a moderator rather than a direct predictor, capturing how this perception conditions the influence of friendliness and trust on customer satisfaction.

The mediating roles of satisfaction and attitude

Satisfaction and attitude emerged as important mediators in translating HRI constructs into revisit intentions. Trust exhibited indirect-only mediation through satisfaction (H3, H4 d), highlighting its foundational role in fostering retention. In contrast, friendliness demonstrated competitive mediation, reflecting the inherent challenge of balancing its relational benefits with potential functional drawbacks (H2c, H4c). The complementary mediation effects of novelty (H2a, H4a) highlight its role as an experiential driver that can enhance customer retention when paired with positive satisfaction and attitudes. These findings illustrate the layered complexity of customer decision-making in robotic service environments and reinforce the need for multi-dimensional approaches in designing effective HRI strategies.

Theoretical and practical contributions

Theoretical contributions

This study makes significant contributions to HRI, service marketing and consumer behaviour literature by refining existing theoretical frameworks and challenging prior assumptions about customer engagement with robotic services. Unlike previous research that primarily applied the S–O–R framework to human-like robots, this study demonstrates its applicability to non-humanoid, hybrid-functional robots, providing a modified theoretical lens for robotic service environments. By integrating S–O–R with the USUS framework, this study provides a more structured understanding of how customers interact with robots that emphasise functionality over anthropomorphic features.

While prior research predominantly examined technology adoption and initial acceptance (e.g. TAM, UTAUT), this study shifts the focus toward sustained engagement, satisfaction and revisit intentions (Davis, 1989; Venkatesh et al., 2003; Yuen et al., 2022). Specifically, it refines the S–O–R framework by demonstrating that functional, emotional and relational dimensions do not operate as isolated factors, but as interdependent drivers of customer engagement. This process-oriented approach challenges traditional models that treat these dimensions as independent predictors of behavioural outcomes (Mkpojiogu et al., 2024).

Moreover, a key theoretical refinement in this study is its extension of the integrated S–O–R–USUS framework to *hybrid-functional robots* (i.e. non-humanoid, task-oriented service robots). Prior studies largely assumed that social bonding mechanisms in humanoid robots are essential for customer trust and satisfaction (Oyedele et al., 2007). However, this study challenges that assumption by demonstrating that non-humanoid robots can foster relational engagement through functional reliability rather than emotional expressiveness. This finding aligns with role congruity theory (Eagly & Karau, 2002), which suggests that robots deviating too far from expected functional roles may face user resistance. This aligns with findings in conservative markets where symbolic brand traits do not always translate into behavioural loyalty, particularly when utilitarian expectations dominate (Al-Hajla et al., 2019). By examining the mediating roles of attitude and satisfaction, the study clarifies that functional efficiency remains dominant in robotic service environments. Still, emotional and relational factors create situational variations in customer responses.

Novelty-seeking and the limits of sustained engagement

This study also challenges conventional assumptions about novelty-seeking in HRI engagement models. Previous

research assumed that novelty consistently enhances engagement (Tussyadiah et al., 2020). However, this study demonstrates that high novelty-seekers experience diminishing satisfaction over time, revealing a critical boundary condition for the Hedonic Adaptation Theory (Frederick & Loewenstein, 1999). Customers who crave novelty have a higher threshold for stimulation and quickly acclimate to novel experiences. Specifically, while novelty sparks initial excitement, high novelty-seekers exhibit a faster decline in satisfaction, requiring continuous innovation to maintain engagement (Chang, 2024). In contrast, low novelty-seeking customers, who do not regularly seek out new experiences, derive substantial delight and satisfaction from the novel encounter, which strongly boosts their revisit intentions. This insight refines prior work by showing that novelty alone does not sustain long-term engagement in robotic service environments.

Trust, rapport, and the complexity of relational dynamics in HRI

Another significant theoretical contribution is the dual role of rapport in robotic interactions. While previous research assumed that rapport-building mechanisms continually strengthen trust in HRI (Nomura & Kanda, 2016), this study finds that rapport paradoxically weakens the trust-satisfaction relationship. This supports Trust-Distrust Duality Theory (Lewicki et al., 1998), which posits that trust and distrust can coexist in relational interactions. However, this study advances that argument by demonstrating that trust formation in robotic service settings follows a different trajectory than in human–human interactions.

Rather than reinforcing trust, excessive relational engagement may create unrealistic expectations of social connectedness that robots cannot fulfil. This challenges prior service marketing research assumptions, which treated rapport as a universally positive factor (Cavedon et al., 2015; Gremler & Gwinner, 2000). Instead, this study highlights a trade-off between functional efficiency and perceived relational authenticity, requiring a complex balance between engagement and credibility in robotic service design.

Refining theories of social perception in HRI

This study also contributes to the ongoing discussions on the role of social perception in HRI. Recent studies indicate that acknowledgment and perceived warmth influence customer engagement with service robots (Frank & Otterbring, 2023). This study extends that argument by showing that acknowledgment, rapport, and trust function differently in non-humanoid robotic contexts, shaping customer revisit intentions through mechanisms distinct from human service encounters.

Furthermore, this study aligns with emerging research on affective technology acceptance, which suggests that positive affect enhances robotic acceptance, while negative affect has mixed effects depending on the measurement approach (Jessup et al., 2023). By integrating affective, cognitive and relational perspectives into a structured framework, this study refines our understanding of customer-robot interactions in service industries, specifically restaurants.

Practical contributions

The findings offer actionable guidance for managers and designers working in robotic service environments. Restaurant managers can leverage these insights to balance friendliness and professionalism in robotic interactions. Robots should exhibit polite and approachable behaviour while maintaining task efficiency to meet customer expectations. High novelty-seekers benefit from periodic updates to robot features, such as modular functionalities or interactive designs, which sustain engagement and prevent hedonic adaptation (Frederick & Loewenstein, 1999). In contrast, low novelty-seekers prefer consistent and reliable interactions that emphasise core functionalities like safety and efficiency (Hlee et al., 2022). Subtle rapport-building mechanisms, such as continuity in interactions or adaptive communication, can foster familiarity without undermining trust (Seo & Lee, 2021).

For designers and coders, the study highlights the importance of creating adaptive algorithms that support context-sensitive rapport-building, enhancing relational warmth without overpromising emotional engagement (Lewicki et al., 1998). Anthropomorphic features should be carefully calibrated to align with operational goals and avoid creating unrealistic expectations (Oğan, 2024). Modular software designs that allow periodic updates can maintain novelty for high novelty-seekers, while high task-oriented performance ensures satisfaction for low novelty-seekers. Safety features, such as hygienic handling and advanced navigation, build trust in restaurant settings, while seamless integration with restaurant management systems improves operational efficiency and provides valuable data for refinement (Edvardsson et al., 2018).

Managers and designers must align robotic features with customer expectations by considering both functional and relational dimensions to optimise customer experience. Robotic systems can enhance customer satisfaction and foster long-term loyalty by integrating functional efficiency, emotional engagement and relational dynamics.

Conclusion

This study advances the understanding of human–robot interactions in service environments by examining how functional, emotional and relational factors work together to shape

customer experience outcomes. By integrating the S–O–R framework with the USUS framework, the research provides a more complete perspective on how service robot features and behaviours influence customer satisfaction, trust and revisit intentions. The findings indicate that these dimensions are interdependent rather than isolated drivers of engagement: for instance, rapport amplifies the effect of a robot’s friendliness on satisfaction, and the thrill of novelty can taper off with repeated exposure. Theoretically, the study bridges human–robot interaction and service marketing literatures, extending traditional adoption models to consider sustained engagement and the complex interplay of social and functional cues. Practically, it offers guidance for service providers deploying robots, highlighting the need to balance operational efficiency with relational warmth. Robotic services should deliver reliable, safe performance while fostering appropriate social interaction to meet customer expectations. These insights contribute an integrated framework for designing customer-centric robotic services that maximise satisfaction and encourage loyalty in hospitality settings.

Limitations and directions for future research

This study is not without limitations. First, all measures were self-reported, which raises the potential for common method bias, social desirability influences as well as the attitude-behaviour gap. Although procedural remedies (e.g. a marker-variable technique) were employed to mitigate bias, future work should consider complementary data (such as observational or behavioural metrics) to validate the self-report findings. For instance, actual return visits or purchase records can verify whether stated intentions translate into repeat patronage. Second, the research was cross-sectional, capturing perceptions at a single point in time. This design limits the ability to infer causality or observe how customer responses evolve. Longitudinal studies are needed to examine temporal dynamics. For example, tracking whether the novelty effect on engagement stabilises or further declines over multiple interactions (Ali et al., 2024; El-Said & Al Hajri, 2022). Third, the sample was drawn from a single regional and cultural context (a Malaysian restaurant setting), which may restrict the generalisability of the results. Cultural norms likely moderate how customers perceive and accept service robots, so cross-cultural research is warranted to test the model in diverse settings (Huang & Liu, 2022). Customer expectations and perceptions of robotic interactions vary between Western and Asian markets, particularly concerning the role of social presence, politeness and emotional engagement in service settings (Huang & Liu, 2022). Fourth, this study focused on a specific service context (casual dining) and a particular type of service robot (a non-humanoid, task-oriented delivery robot). The findings may not fully apply to other industry settings or to robots with different designs. Future studies should therefore examine hybrid human–robot

service models where robot assistants work alongside human staff, to see how such arrangements influence perceived efficiency, service warmth and overall satisfaction (Wang et al., 2025). Similarly, researchers could investigate the impact of more anthropomorphic robot designs on customer trust and comfort, as the optimal degree of human-likeness in service robots remains an open question (Tussyadiah et al., 2020). Fifth, the study found that safety had no significant impact in revisit intentions, perhaps because basic safety is now assumed by customers; future research could examine if this holds in scenarios with higher perceived risk or different cultural settings. Finally, the study omitted ‘Societal Impact’, the fourth dimension of the USUS framework, thereby excluding broader societal-level considerations from the model. Leaving out this factor creates a gap in understanding the full spectrum of impacts. Future research should integrate the Societal Impact dimension to provide a more complete evaluation of service robot implementations, examining how these technologies affect not just individual customers but also wider society.

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Data Availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Competing interests The authors declare that they have no competing interests.

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