Exploring the impact of human-computer interaction on service robot adoption intention in the service industry

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Abstract:

Recent advancements in artificial intelligence have driven the widespread adoption of service robots across various service sectors, particularly in consumer-facing tasks to enhance customer experience. However, how service contact level (low vs. high) and human-computer interaction (HCI) role orientation (partner vs. master-servant) collectively influence consumer adoption remains underexplored. This paper addresses this void through three experiments in the hospitality and restaurant settings. Findings reveal that in low-contact settings, a master-servant HCI fosters cognitive trust and adoption, while in high-contact contexts, a partner-oriented HCI builds emotional trust and encourages adoption. Task complexity also moderates this relationship: high-complexity tasks benefit from a master-servant model in low-contact scenarios, while low-complexity tasks favor a partner model in both contact conditions. This paper contributes a novel "contact level–HCI relationship" alignment framework, offering theoretical insights and practical guidance for enhancing consumer acceptance and integration of service robots.

Keywords: Service robots, Service contact level, Human-robot interaction, Cognitive Trust, Emotional Trust

1. Introduction

The rapid technological development of robotic devices integrated with artificial intelligence (AI) and machine learning is fundamentally transforming service experiences, making them more efficient, adaptive, and innovative (Knani et al., 2022; So et al., 2024). Service robots are increasingly deployed across diverse sectors, particularly in hospitality and food and beverage contexts, due to their ability to deliver consistent, accurate, and scalable service interactions (Kim et al., 2022; Liao & Huang, 2024). Recent industry reports further underscore this trend. For instance, the Transamerica Institute (2025) indicates that 72% of companies currently use or plan to adopt AI and robotics to augment their workforce, while evidence from China suggests rapid acceleration in AI investment and deployment (Feifei, 2025). These developments highlight the strategic importance of service robots in enhancing operational efficiency, competitiveness, and service innovation.

In response to this technological shift, academic interest in AI-driven service technologies has grown substantially (Chi et al., 2023; So et al., 2024; Xu et al., 2023). Service robots are defined as autonomous and adaptive systems capable of interacting with customers and delivering services through intelligent, interface-based communication (So et al., 2024; Wirtz et al., 2018). Unlike traditional automated systems, service robots are distinguished by their ability to operate within socially interactive environments, employing human-like gestures, emotional expressions, and relational cues (Brengman et al., 2021; Söderlund & Oikarinen, 2021). This capability enables firms to enhance customer engagement and competitive advantage. Accordingly, service robots exert multi-level impacts—at the micro level (individual customer experience), meso level (service markets), and macro level (societal transformation)—affecting a wide range of stakeholders (Wirtz et al., 2018).

Despite this growing interest, prior research has predominantly focused on simplified dichotomies such as anthropomorphic versus non-anthropomorphic designs (Chen et al., 2020), robots versus humans (Sheehan et al., 2020), or humans versus objects (Qin, 2020). While informative, these binary classifications provide a limited understanding of the complex interactional dynamics underlying human–robot interaction (HCI). In particular, they overemphasize physical appearance while neglecting how consumers interpret and engage with service robots within varying service contexts characterized by differences in interaction frequency, duration, and relational depth. These contextual variations play a critical role in shaping consumer expectations, evaluations, and behavioral responses.

A key limitation in existing literature is the insufficient attention given to the social role attribution of service robots and its implications for consumer behavior. Service robots may be perceived as occupying different social roles, such as servants (task-oriented and hierarchical) or partners (collaborative and relational), yet the influence of these role perceptions on adoption intention remains underexplored (Sun et al., 2023). Similarly, the role of service contact level as a contextual factor influencing consumers' cognitive and affective responses to service robots has received limited scholarly attention (Chen & Girish, 2023). Existing models often assume that similar robotic platforms yield uniform responses, overlooking the possibility that consumer interpretations vary significantly depending on interaction context and role-based meaning-making processes.

In early stages of technological diffusion, adoption intention is widely used as a proxy for actual behavior due to limited observable usage data. Accordingly, this study defines adoption intention as an individual's deliberate and reasoned willingness to engage with or use a service robot in the future (Yuan et al., 2024). Importantly, this study argues that adoption intention is not solely driven by aesthetic or functional evaluations, but also by socially constructed interpretations arising from interaction contexts and role assignments. Specifically, the same service robot may be interpreted differently depending on whether it is perceived as a servant or a partner and whether the interaction occurs in low-contact or high-contact service settings.

To address these theoretical and empirical gaps, this study develops an integrated framework grounded in human–computer interaction (HCI) and social role theory. The framework examines: (1) the interaction between HCI role orientation and service contact level in shaping adoption intention; (2) the mediating role of cognitive and emotional trust; and (3) the moderating role of task complexity. By explicitly modelling these mechanisms, the study advances a more nuanced understanding of how consumers interpret and respond to service robots beyond surface-level characteristics. Accordingly, this study addresses the following research questions:

RQ1: How do service contact level and HCI role orientation jointly influence consumers' adoption intention toward service robots?

RQ2: How do cognitive and emotional trust mediate the relationship between HCI role orientation and adoption intention?

RQ3: How does task complexity moderate the relationships between HCI, trust, and adoption intention?

By integrating HCI with social role theory, this study offers a novel conceptual lens to examine how technological interfaces and socially constructed role expectations jointly shape trust formation and adoption behavior. While HCI explains how users interact with technology interfaces, social role theory elucidates how individuals interpret relational expectations within these interactions. This theoretical integration provides a more comprehensive explanation of consumer responses to service robots, particularly in varying service contexts.

The study contributes to the literature in several ways. First, it advances service robot research by adopting a contextual and role-based perspective, demonstrating how perceptions of the same technology vary across different service contact conditions. Second, it highlights the central role of trust as a dynamic mechanism, showing how interaction patterns influence both cognitive and emotional trust formation. Third, the findings provide important managerial insights, enabling organizations to design service robots and interaction strategies that align with contextual service requirements, optimize resource allocation, and enhance customer experience. In particular, the study underscores the importance of strategically managing service contact to facilitate the transition from cognitive to emotional trust, thereby strengthening adoption intention.

The remainder of the paper is structured as follows. The next section presents the theoretical framework and hypotheses, followed by the methodology, results, and discussion. The paper concludes with implications, limitations, and directions for future research.

2. Theoretical Background

2.1. The Anthropomorphized Nature of Service Robots

The International Organization for Standardization (ISO, 2021) characterizes robots as automated devices endowed with programming capabilities that execute multidimensional activities independently in dynamic operational environments. Service robots operate autonomously as agents within service contexts, adapting their behaviours in real time during consumer interactions (So et al., 2024). Over time, service robots have evolved from hardware-centric tools to intelligent, adaptive systems capable of complex social interaction, reflecting significant advancements in artificial intelligence and machine learning technologies (Rust & Huang, 2014). For example, robots such as DARwIn-OP and Pepper, alongside virtual assistants like Siri and Google Assistant, illustrate the diversity of service robots, ranging from non-humanoid to humanoid forms (So et al., 2024; Wirtz et al., 2018). A key driver of this evolution is the incorporation of anthropomorphic attributes, which enable robots to exhibit perceived intentionality, emotional responsiveness, and goal-directed behavior (Huang et al., 2021).

The evaluation of anthropomorphism in service contexts has gained increasing scholarly attention in recent years (Croes & Antheunis, 2021; So et al., 2024; Sun et al., 2023). Early research primarily focused on external anthropomorphic cues, such as human-like appearance and physical features, which enhance perceived human likeness (Aggarwal & McGill, 2007). However, recent studies suggest that such surface-level characteristics are insufficient to meet evolving consumer expectations for deeper and more meaningful interactions. Instead, there is growing emphasis on internal anthropomorphic cues, including perceived intentionality, empathy, and emotional responsiveness, which play a more critical role in shaping user perceptions and experiences (Sun et al., 2023).

Building on this perspective, the concept of social anthropomorphism has emerged, reflecting the extent to which robots are perceived as capable of engaging in socially meaningful interactions (Schweitzer et al., 2019). In this context, anthropomorphism extends beyond appearance to encompass relational and behavioural attributes that influence how users interpret and respond to service robots. Accordingly, anthropomorphic perception can be understood as a cognitive process through which users assign social meaning to technological agents.

From a social psychology perspective, role theory posits that individuals' behaviours and expectations are shaped by socially defined roles, contextual norms, and interactional goals (Marin et al., 2006). Applying this lens to human–robot interaction, consumers interpret their interactions with service robots by assigning socially meaningful roles based on contextual cues and interaction patterns. Specifically, service robots may be perceived as "servants," characterised by task-oriented compliance and hierarchical dependence, or as "partners," reflecting collaboration, relational equality, and co-creation (Sun et al., 2023). The designation of "partner" implies a co-producer of value, often associated with roles such as co-worker or teammate, whereas "servant" denotes a more subordinate, task-execution role aligned with traditional service hierarchies.

Importantly, these role attributions are not merely descriptive but have significant implications for consumer evaluations and behavioral responses. The roles assigned to service robots influence how users assess service quality, develop trust, and form emotional connections with the technology (Aggarwal & McGill, 2012). Thus, this study conceptualizes anthropomorphic perception as an antecedent cognitive mechanism that facilitates social role assignment, which in turn shapes both cognitive and emotional responses toward service robots. By positioning anthropomorphism in this way, the study moves beyond treating it as a static design feature and instead frames it as a dynamic interpretive process underlying human–robot interaction.

2.2. Service Contact Levels

Service contact refers to the extent of interaction between the service provider and the customer during service delivery. In this study, service contact level is operationalized through interaction frequency, duration, and intensity, capturing both functional and relational aspects of HCI.

Unlike prior studies that treat service contact as a static characteristic, this research conceptualizes it as a contextual mechanism that influences how users interpret and respond to robot roles. In low-contact settings, limited interaction reduces relational cues, leading users to rely on functional evaluations. In contrast, high-contact settings provide richer interactional signals, enabling relational interpretation and emotional engagement.

Service contact refers to the reciprocal interaction between service providers and customers that occurs throughout the service delivery process (Bearden et al., 1998).

Early research conceptualized service contact as a *"two-way dynamic interaction process between service personnel and consumers"* (Surprenant & Solomon, 1987). Extending this perspective, subsequent studies emphasize that service contact is not limited to face-to-face encounters but encompasses a broader range of interactions enabled by technological and digital interfaces (Bitner et al., 2005). For instance, Meuter et al. (2005) demonstrate that transient and infrequent interactions often occur in contexts where consumers do not anticipate ongoing engagement with service personnel. Accordingly, service contact should be understood as a continuum of interaction intensity, rather than a discrete or static phenomenon.

The increasing integration of artificial intelligence in service settings has fundamentally reshaped the consumer–service provider relationship, which is now increasingly mediated through human–computer interaction (HCI) (Kim et al., 2013; So et al., 2024). In technology-enabled environments, particularly those involving service robots, the interaction itself becomes a central component of the service experience, as robots simultaneously function as both the service interface and the service provider (Wirtz et al., 2018). Within this context, service contact can be further differentiated based on the nature of interaction and engagement. For example, Huang and Rust (2021) distinguish between trust-based generative service models and experience-based supported service models, reflecting different levels of interaction depth and relational engagement. Building on this, Bitner and Wang (2014) define service contact as *"any discrete interaction between the consumer and the service provider concerning the core service offering,"* highlighting its central role in shaping service experiences.

Marketing literature further suggests that consumer evaluations and behavioral intentions are formed across multiple stages of the service process, including pre-purchase decision-making, the service encounter, and post-consumption evaluation (Ahmed et al., 2025; Gamage et al., 2025). However, the integration of service robots into frontline service encounters necessitates a more precise and contextually grounded conceptualization of service contact, particularly in relation to human–robot interaction.

To address this gap, the present study conceptualizes service contact level as a multidimensional construct, operationalized through three key dimensions: interaction frequency (how often consumers interact with the robot), interaction duration (the length of each interaction), and interaction intensity (the extent of task involvement and emotional engagement during the interaction). This operationalization captures both the functional and relational aspects of HCI, providing a more comprehensive measure of interaction depth.

Unlike prior research that treats service contact as a static characteristic, this study conceptualizes it as a dynamic contextual mechanism that shapes how consumers interpret and respond to service robots. Drawing on role theory and social cognition perspectives, varying levels of service contact provide different degrees of relational cues that influence social role attribution. In high-contact settings, frequent, prolonged, and intensive interactions enable consumers to observe consistent behavioral patterns, thereby increasing the likelihood that robots are perceived as socially capable agents (e.g., partners). In contrast, low-contact settings, characterized by brief and utilitarian interactions, limit relational cues and reinforce perceptions of robots as functional, subordinate entities (e.g., servants).

Accordingly, service contact level functions not only as a contextual variable but also as a mechanism through which users construct and assign social roles to technological agents. Building on this foundation, the present study examines how varying service contact levels (high vs. low) interact with anthropomorphic role orientations in HCI (partner vs. servant) to influence consumer adoption of service robots. Furthermore, it investigates the mediating role of cognitive and emotional trust in translating these interactional dynamics into behavioral outcomes.

2.3. Cognitive and Emotional Trust

The social exchange theory of social psychology provides a robust framework for understanding the interpersonal dynamics underlying relationship development (Cook & Rice, 2006). Extending this perspective to technology-mediated environments, trust emerges as a fundamental mechanism governing interactions between users and intelligent systems, particularly within human–computer and human–robot interaction contexts (Xiao et al., 2025). In service settings, consumer trust is generally defined as a belief or confidence in the reliability and integrity of a service provider (Mahottama & Giantari, 2025). Building on this foundation, the present study adopts a dual-dimensional conceptualization of trust, distinguishing between cognitive trust and emotional trust as two complementary yet distinct evaluative processes.

Cognitive trust is grounded in rational evaluation, whereby consumers assess the competence, reliability, and predictability of a service agent based on observable performance indicators (Li et al., 2025). In the context of service robots, this form of trust is reinforced when robots demonstrate accuracy, consistency, and task efficiency, thereby signaling functional capability and dependability (Diab & Demiris, 2025). In contrast, emotional trust is rooted in affective responses and reflects a sense of psychological comfort, relational warmth, and perceived social connection arising from interaction experiences (Jiang et al., 2025; Khan et al., 2025). This dimension of trust is shaped by social and relational cues, such as empathy, responsiveness, and perceived emotional intelligence.

While early studies on service robot adoption predominantly relied on technology acceptance models such as TAM and UTAUT (e.g., Caić et al., 2020; Conti et al., 2017), recent research has shifted towards recognizing the inherently social and relational nature of human–robot interaction. Consequently, social exchange theory has been increasingly employed to explain how reciprocal interactions and perceived relational benefits influence trust formation and subsequent adoption behavior (Homans, 1958; Kim et al., 2022). This shift reflects a broader movement from purely functional evaluations of technology towards a more holistic understanding that incorporates relational and emotional dimensions.

Building on this theoretical foundation, the present study applies the dual-dimensional model of trust proposed by McAllister (1995) to explain how social role assignment operates as a key mechanism linking HCI to trust formation. Specifically, the attribution of social roles—such as servant or partner—provides users with normative expectations and behavioral scripts, which guide their evaluation of the robot. When a robot is perceived as a servant, users tend to prioritize functional performance, thereby strengthening cognitive trust. Conversely, when a robot is perceived as a partner, relational and collaborative cues become more salient, fostering emotional trust.

In addition to role attribution, service contact level further shapes the development of trust by influencing the availability and richness of interactional cues. Drawing on social exchange theory, increased service contact—characterized by frequent, prolonged, and intensive interactions—provides users with stronger diagnostic information regarding the robot's competence and reliability, thereby enhancing cognitive trust. Simultaneously, repeated and socially rich interactions facilitate emotional familiarity and perceived relational closeness, which strengthen emotional trust. In contrast, low-contact conditions limit information exchange and reduce opportunities for relational bonding, thereby constraining the development of both cognitive and emotional trust.

These mechanisms collectively explain how trust operates as a critical mediating process linking HCI features to adoption intention. By integrating anthropomorphic perception, social role assignment, and trust formation, the study establishes a coherent theoretical pathway: anthropomorphism → social role assignment → cognitive and emotional trust → adoption intention. This perspective moves beyond traditional dichotomies in anthropomorphism research, which have historically emphasized appearance-based distinctions, and instead conceptualizes anthropomorphism as a process of mind perception driven by relational and contextual cues.

Accordingly, the dual-trust framework provides a comprehensive lens for understanding how users develop both functional confidence and emotional attachment to service robots. By demonstrating that trust is shaped not only by technological performance but also by socially constructed role expectations and interaction contexts, this study offers a more nuanced and theoretically grounded explanation of service robot adoption.

3. Theoretical Model and Hypotheses Development

3.1. Theoretical Model

The development of service robots necessitates anthropomorphic features and quasi-social interaction capabilities to foster human trust and acceptance in HCI (Wirtz et al., 2018). Different service contexts require service providers to assign specific social roles to robots to facilitate significant interactions between humans and machines (Blaurock et al., 2022). Van Doorn et al. (2017) assert that successful HCI must attain a balance between the dimensions of "*efficiency*" and "*experience*". The fundamental features of HCI are human-computer interaction and emotional engagement. Hence, this paper will concentrate on the dual social roles of service robots as partners or servants and two dimensions of trust: cognitive trust and emotional trust (McAllister, 1995).

The reason is that interacting with highly anthropomorphic robots can be compared to interpersonal communication; hence, building a solid and reliable trust relationship between humans and machines is crucial for adopting service robots (Baker et al., 2018). Therefore, we develop a research model that initiates with the service contact level, followed by the human-computer relational orientation, with cognitive trust and emotional trust serving as intermediary variables between these elements. Figure 1 illustrates this theoretical model.

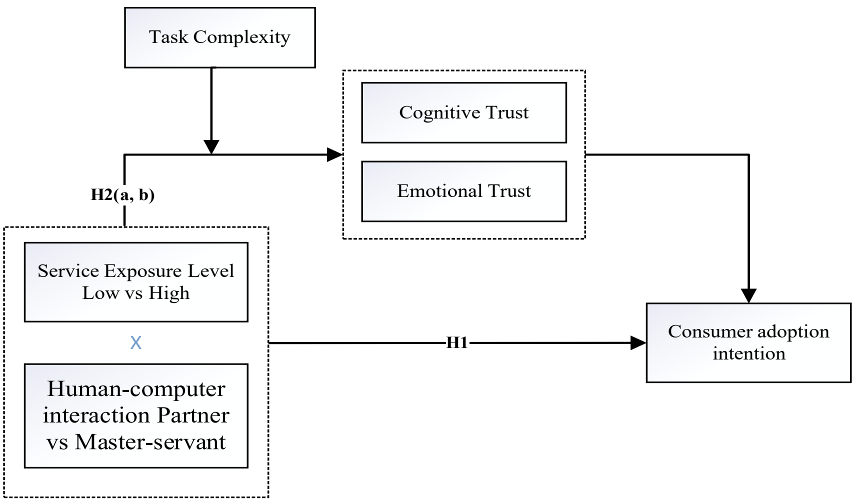


Figure 1. Proposed Theoretical Model

3.2. Hypotheses Development

In HCI, service robots project an automated social presence by assuming diverse social roles, enhancing human-like social interaction (Van Doorn et al., 2017). Similarly, Shechtman and Horowitz's (2006) study indicates that varying intensities of interpersonal contact among people may result in different behavioral paradigms. Therefore, examining the extent of service engagement in HCI is vital. According to social response theory, individuals instinctively attribute social roles to machines (Nass & Moon, 2000; Sanchez et al., 2025). Consequently, service robots align more closely with consumers' initial expectations for integrating AI technology when they assume a distinct servant role rather than a partner role. The dynamic between master and servant inherently suggests a power imbalance (Kim & Kramer, 2015). When the level of service interaction is minimal, this direct variation in status diminishes customers' perception of the technical uncertainties and anxiety associated with service robots (Mende et al., 2019). Furthermore, interactions within a master–servant dynamic necessitate customers to issue directive commands to service robots, potentially increasing cognitive effort. Cognitive load theory emphasizes minimizing this mental burden to enhance users' problem-solving efficiency and overall interaction quality (Sweller, 1988).

This study posits that customers may have a limited understanding of service robots' full capabilities in low-contact service scenarios (cf. Pitardi et al., 2024). It contends that the one-way instructional mode in the master-servant dynamic aligns more closely with consumer adoption expectations at this low level of service contact than a partnership model (e.g., Shin et al., 2024). However, when consumers engage extensively with service robots, these robots have greater opportunities to foster quasi-social relationships with them (Balaji et al., 2024). In this context, the service robots assume the role of a partner and possess distinct advantages over that of a servant (Balaji et al., 2024). It can convey warmth and empathetic language through dialogues that mirror the dynamics of friendship, thereby facilitating emotional feedback that addresses consumers' social belonging needs (Pizam et al., 2024). Furthermore, as service quality interactions improve, customers' impressions and familiarity with service robots will progressively increase (e.g., Shin et al., 2024). Consequently, HCI within a partnership may lead to greater co-creation of value than a master-servant dynamic, since partners will proactively adjust to one another's behaviours (Yuan et al., 2025). Accordingly, we developed the following hypotheses:

H_1: The level of service contact and the relationship between HCI have an interactive impact on consumers' adoption intention of service robots.

H_{1a}: When the level of service contact is low, a master-servant interaction style enhances consumers' adoption intention of service robots more than a partner-style interaction.

H_{1b}: When the level of service contact is high, a partner-style interaction increases consumers' adoption intention of service robots more than a master-servant style.

The social exchange theory is frequently referenced in the context of the reciprocal dynamics of service interactions in interpersonal communication (Kim et al., 2022). It assumes that individuals exchange resources in mutually advantageous interactions by evaluating costs and benefits, anticipating favorable outcomes. Service robots represent a highly anthropomorphic and transformative technology distinct from prior products, often perceived as social entities akin to humans, making social exchange theory pertinent to this context (Pitardi et al., 2024). The interaction between consumers and service robots closely parallels human interaction, as the process of HCI encompasses not only resource exchange but also the objective of resource acquisition (Shin et al., 2024). Therefore, social exchange theory finds relevance in the realm of HCI, laying a theoretical foundation to elucidate the dynamics between consumers and service robots and the engagement behaviors exhibited by both entities during service encounters (Kim et al., 2022). Furthermore, the principle of reciprocity inherent in the social exchange theory serves as a foundation for fostering trust and commitment within these relationships (Ahn et al., 2025).

This paper delineates two forms of trust: cognitive trust, which reflects consumers' perceptions of a service robot's competence and reliability in performing service tasks, and emotional trust, which arises from consumers' subjective feelings of safety, comfort, and emotional reassurance during human–robot interactions (Anzabi &

Umemuro, 2023). When consumer interaction with service robots is minimal, emotional connections are absent, leading consumers to depend primarily on objective assessments of robotic functions (Xu et al., 2020). The technical trust model indicates that, during initial HCI, consumer trust predominantly hinges on the reliability of performance (Lee & See, 2004). The master-servant dynamic between humans and machines is a task-oriented social relationship wherein consumers anticipate compliance with directives and prompt responses from service robots (Fiestas Lopez Guido et al., 2025). This focus on task efficiency and quality of task completion prompts consumers to prioritize cognitive trust when interacting with service robots, thereby shaping their preference for employing robots in task-executing roles (Park, 2020).

Conversely, when consumers engage more extensively with service robots, they encounter greater opportunities to perceive the anthropomorphic cues they convey during interactions (Shin et al., 2024). However, when positioned as partners, service robots can elicit emotional projection from consumers through personalized interactions, empathetic communication, and behaviours similar to those of friends, thereby fostering positive feelings of warmth and companionship (Nass & Moon, 2000). A high level of service contact fosters the essential conditions for emotional trust in human-machine relationships, leading to the establishment of a "*relationship history*" between consumers and service robots during frequent interactions, thereby enhancing consumer self-disclosure and emotional connection (Wang et al., 2016). This ongoing emotional reciprocity may foster customers' emotional connection with the service robot's benevolence and honesty, increasing the likelihood of adopting the robot as a partner via emotional trust. Consequently, the following hypotheses are posited:*H_{2a}: When consumers have low levels of service exposure, the master-servant HCI dynamic enhances cognitive trust more than a partner-style interaction, thereby increasing consumers' adoption intention of service robots.*

H_{2b}: When consumers have high levels of service exposure, partner-based HCI fosters emotional trust more than a servant-role interaction, thereby increasing consumers' adoption intention of service robots.

3. Methodology

4.1. Method Selection and Manipulation

This study adopts a scenario-based experimental design, in which participants are exposed to structured service scenarios and asked to evaluate their responses. Building on prior research in service robot and HCI contexts (Min et al., 2016; Sun et al., 2023; Roesler et al., 2024), the study employs situational simulations within a scenario-based framework, enabling the systematic investigation of consumer decision-making under controlled hypothetical conditions. Scenario-based experiments are widely used in service robot research, particularly where real-time deployment is constrained by technological and ethical considerations, as they allow researchers to isolate causal relationships while maintaining a reasonable degree of contextual realism. This approach ensures high internal validity through controlled manipulation of key variables, while also facilitating the examination of cognitive and emotional processes relevant to early-stage technology adoption.

To comprehensively examine the theoretical model, the study comprises three experiments, each designed to investigate distinct aspects of the proposed relationships across different service contexts. Experiment 1, conducted in a hotel setting, tests the interaction effect of service contact level and HCI role orientation on adoption intention. Experiment 2, situated in a restaurant context, examines the mediating role of cognitive and emotional trust. Experiment 3, conducted in a supermarket context, investigates the moderating effect of task complexity. These experiments vary in contextual setting, manipulated variables, and analytical focus, thereby providing a form of methodological triangulation that enhances the robustness, internal validity, and generalizability of the findings across diverse service environments (Sun et al., 2023).

Participants were recruited through the Credamo online data collection platform, which provides access to diverse consumer samples. To ensure relevance to the experimental scenarios, eligibility criteria required participants to have prior experience in service contexts such as hotels, restaurants, or retail environments. The use of multiple independent samples across the three experiments further strengthens the generalizability of the results by capturing a broad representation of typical service consumers.

To ensure data quality and reliability, the study incorporated multiple screening procedures, including attention-check questions, response time filtering, and systematic data cleaning. These measures are consistent with established experimental research practices and were implemented to identify and remove inattentive or low-quality responses, thereby enhancing the credibility of the dataset.

The experimental scenarios utilized image-based visual stimuli to depict service interactions. While video-based stimuli may offer higher ecological realism, image-based scenarios are commonly employed in experimental research due to their ability to maintain tight control over variable manipulation and reduce extraneous influences (Min et al., 2016; Sun et al., 2023). This approach is particularly appropriate for examining cognitive and evaluative constructs, such as trust and adoption intention, where controlled exposure to stimuli is essential for isolating psychological responses. Nevertheless, this methodological choice is acknowledged as a limitation, and future research is encouraged to employ video-based or field experimental designs to further enhance ecological validity.

4.1.1. 1st Experiment

We preliminarily investigate the interacting effects of service contact level and the HCI connection on customers' adoption intention toward service robot. Focusing on the hotel check-in context and the deployment of robotic services, this paper aimed to assess participants' adoption intention toward service robot by manipulating interaction levels (as depicted in Figure 2) and varying role-based stimuli. The delivery process involving robots in a face-to-face capacity is characterized by minimal or absent robotic assistance, resulting in limited direct engagement during the service. Conversely, the high-level service contact group benefits from continuous support and interaction with robots at every stage, ensuring deeper engagement throughout the process. The primary effect is tentatively substantiated in this manner. Participants were initially prompted to envision staying at a hotel for business or leisure purposes. They were presented with images and informed that the hotel would employ the service robot "*Rupert*" to assist with various services. Subsequently, the low-level service contact group was instructed that hotel staff would handle the check-in process, directing participants to navigate to their rooms autonomously via the route designated by Rupert. Conversely, the high-level service contact group was informed that "Rupert" would manage the check-in process, guiding and accompanying participants to their rooms.

Figure 2. Service robot "*Rupert*" servant and partner services

4.1.2. 2nd Experiment

In experiment 2, the experimental materials were altered from the context of hotel check-in and service provision to that of restaurant ordering recommendations and food delivery, as mentioned in Figure 3.

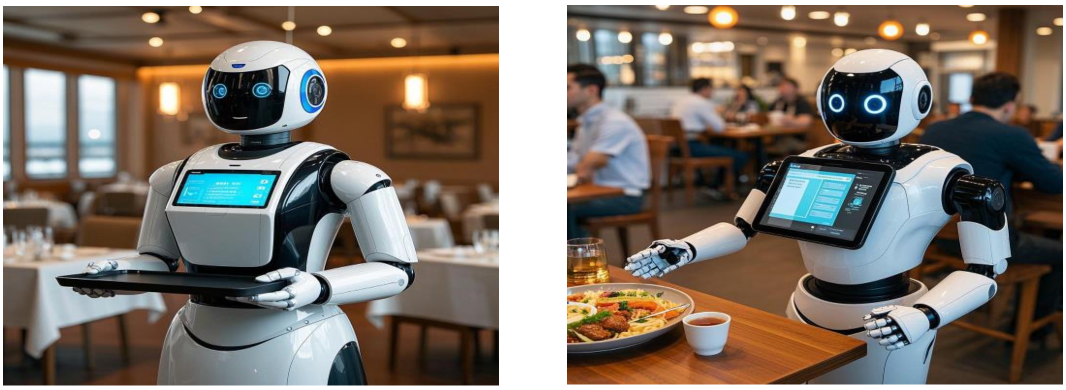


Figure 3. Service robot "Rupert" delivering and ordering food

Particularly, experiment 2 commenced by examining the ordering role, contrasting the functions of restaurant staff with those of service robots. The differing salutations—addressing participants as adults vs. friends—and the tonal variations—ranging from mature to lively voices—elicited distinct perceptions regarding HCI relationships. This approach aimed to substantiate the main and mediating effects under investigation. In this way, the main effect was re-evaluated, and the mediating role of trust—distinguishing between cognitive and emotional trust—in the interplay of different HCI modes on consumers' adoption intention of service robots was examined.

Participants were initially prompted to envision dining at a restaurant. They were presented with images and informed that the hotel would employ the service robot "*Rupert*" to assist them. Subsequently, those in the low-level service contact group were notified that "*Rupert*" would solely be responsible for service during the food delivery phase and would depart once the food had been delivered. The high-service contact group was informed that "*Rupert*" will facilitate services throughout the ordering process. Beyond merely documenting the selections, they proactively inquired about taste preferences and suggested distinctive dishes. Furthermore, during the delivery phase, they will take the opportunity to present the dishes to the participants.

4.1.3. 3rd Experiment

Experiment 3 establishes a scenario in which service robots assist and guide consumers throughout their shopping experience, as shown in Figure 4.

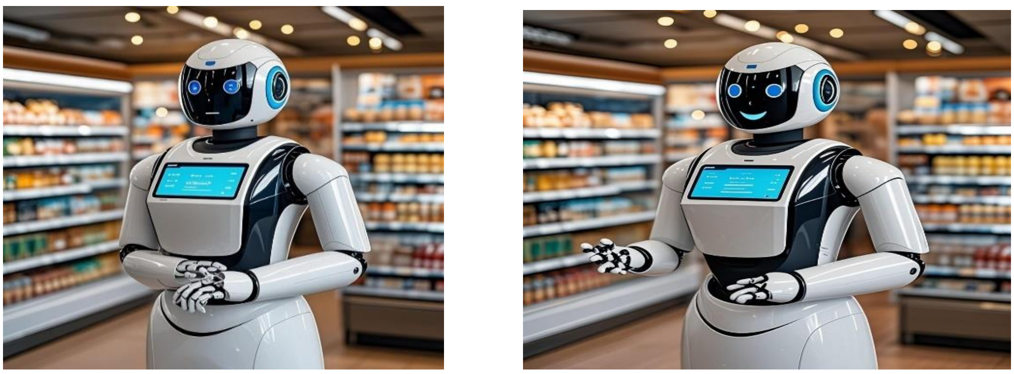


Figure 4. Service robot "Rupert" Servant and Partner style

The contextual framework of the HCI dynamic aligns with the manipulated content established in Experiment 2. Our experiment 3 commences with the inherent challenges associated with the shopping guide service task offered by the service robot, aiming to raise participants' awareness of the intricacies involved in various tasks. Participants' awareness was activated at the service contact level by introducing the scope of shopping guide services that the service robot could provide throughout the supermarket purchasing process.

Participants were initially prompted to envision themselves as frequent shoppers at a supermarket near their residences. They were then presented with images and informed that the supermarket would introduce a service robot named "*Rupert*" to assist consumers with shopping guidance. The high-service contact group was informed that the supermarket had implemented the service robot "*Rupert*" across all categories, including beverages, snacks, cosmetics, home appliances, and other sections. Upon purchasing items across various sections of the supermarket, customers received assistance from "*Rupert*," who offered guidance throughout their shopping experience. Upon completing the three experiments, participants were asked to answer a manipulation test question designed to assess their perception of the interaction with the service robot "*Rupert*" throughout the task. This was measured on a 7-point scale, where 1 indicated minimal HCI, and 7 represented a significant level of HCI, thereby evaluating the effectiveness of manipulating the service contact level. Upon completion of the three experiments, participants were asked to answer a manipulation test question designed to assess their perception of the role of the service robot "*Rupert*" in the consumption process.

Similarly, building on the work of Li et al. (2024), this study adopts their validated scale to investigate the mediating role of trust—encompassing both cognitive and affective dimensions—in the context of human-robot interaction. The three components of cognitive trust include: "I trust that the service robot will deliver professional service in the task," "I trust that the service robot possesses the interaction capability to fulfil the task requirements," and "I trust that the service robot will offer excellent service." The three components of affective trust include the statement, "I trust that the service robot will provide warmth and care during the task." "I have confidence that the service robot will address my service requirements," and "I have confidence that the service robot will exhibit friendliness and enthusiasm." This paper also draws on the task complexity measures developed by Chernikova et al. (2016) and Giessner et al. (2020), adapting their measurement scales to fit the specific contextual parameters of the present study. In the assessment of task complexity, four distinct criteria are delineated: first, the shopping guide task necessitates the service robot's utilization of highly intricate technologies or skills; second, it compels the robot to engage in substantial cognitive processing regarding the customer's unique shopping context; third, it requires the robot to gather and evaluate a considerable volume of information beyond the mere product; and fourth, it is characterized as a notably demanding endeavor for the service robot. Each of these criteria is evaluated using a 7-point scoring system.

5. Analysis and Results

Exploratory factor and reliability analysis

All constructs were measured using validated multi-item scales adapted from prior literature. To assess construct validity and reliability, both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were conducted.

Prior to factor extraction, the suitability of the data for factor analysis was confirmed. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.881, exceeding the recommended threshold of 0.50, while Bartlett's test of sphericity was significant ($\chi^2 = 644.89$, $df = 15$, $p < 0.001$), indicating the presence of sufficient correlations among variables and supporting the appropriateness of factor analysis.

Principal component analysis was employed, resulting in the extraction of two factors that together explained 68.690% of the total variance, exceeding the recommended threshold of 60% and indicating strong construct validity. These factors correspond to the theoretical dimensions of cognitive trust and emotional trust, comprising a total of six items. Factor loadings (Table 1) ranged from 0.617 to 0.877.

Although a small number of items exhibited loadings slightly below 0.60, they were retained based on their theoretical relevance and acceptable overall reliability.

Reliability analysis further supported the measurement model, with Cronbach's alpha values of 0.766 for cognitive trust and 0.768 for emotional trust, both exceeding the acceptable threshold of 0.70. Similarly, the dependent variable, adoption intention, demonstrated satisfactory internal consistency (Cronbach's $\alpha = 0.698$).

Subsequently, confirmatory factor analysis was conducted to further validate the measurement model. Composite reliability (CR) values ranged from 0.796 to 0.870, exceeding the recommended threshold of 0.60. The Average Variance Extracted (AVE) values met the standard criterion of 0.50 for all constructs except cognitive trust (AVE = 0.476). However, this was considered acceptable given that its factor loadings exceeded 0.50 and its CR value remained above the recommended threshold, consistent with established methodological guidelines (Fornell & Larcker, 1981; Boley et al., 2014).

Discriminant validity was assessed using the Fornell–Larcker criterion, which requires that the square root of the AVE for each construct exceeds its correlations with other constructs (Fornell & Larcker, 1981; Shah et al., 2024). The results, presented in Table 2, confirm that this condition is satisfied, indicating adequate discriminant validity among the latent variables.

Overall, the measurement model demonstrates satisfactory levels of reliability, convergent validity, and discriminant validity, thereby supporting its suitability for subsequent structural analysis.

Table1. Results of Measurement Model Analysis

Variables	Factor Loadings	Cronbach's α	AVE	CR
Standard	>0.5	>0.7	>0.5	>0.6
Cognitive Trust		0.766	0.570	0.796
Item 1	0.828			
Item 2	0.802			
Item 3	0.617			
Emotional Trust		0.768	0.587	0.810
Item 4	0.726			

Item 5	0.780			
Item 6	0.790			
Adoption Intention		**0.698**	0.769	0.870
Item 7	0.877			
Item 8	0.877			

Table 2. Results of Discriminant Validity Test

Variables	Cognitive Trust	Emotional Trust	Consumer Adoption Intention
Cognitive Trust	0.888		
Emotional Trust	0.689	0.873	
Consumer Adoption Intention	0.644	0.585	0.853

5.1. 1st Experiment

5.1.1. Procedure

At the outset of experiment 1, a 2 (low vs. high service contact) × 2 (servant-like vs. partner-like robot interaction) experimental design was utilized to investigate consumer responses to human-robot interactions. Initially, the minimal sample size necessary for the experiment was 128, as determined by G*power 3.1 (effect size 0.25, significance level 0.05, statistical test power 0.8). In this study, research samples were collected via the commercial data acquisition system of the Credamo platform. A dual quality control procedure comprising attention-check items and response time filtering was employed to ensure data integrity. After data cleaning, 225 valid experimental responses were retained for analysis. The characteristics of the sample revealed a gender distribution of 58.2% (131) males and 41.8% (94) females, with a mean age of 34.36. Furthermore, the participants' highest level of education was undergraduate (23.1%, 52 individuals), followed by associate degree (22.7%, 51 individuals). The participants' highest monthly income was between 3,500 and 10,000 yuan (46.2%, 104 individuals), followed by between 10,000 and 20,000 yuan (24.0%, 52 individuals).

In this experiment, drawing on the methodology employed by Choi et al. (2022), the level of service exposure was systematically manipulated through a situational imagination task. Participants were asked to envision varying degrees of interaction with a service robot during the hotel check-in process. Specifically, participants in the low-level service contact group were presented with scenarios in which minimal or no interaction with the service robot occurred across key service stages: the check-in phase (choice between hotel staff or robot assistance), the guided check-in process (robot-provided directions vs. full accompaniment), and the item delivery stage (robot drop-off vs. direct handover). In these scenarios, the extent of direct contact or engagement with the robot was deliberately limited to simulate low-level service interaction. The high-level service contact group was served and accompanied by robots throughout all stages of the service process for high-level interaction. Apart from the variation in service contact levels between the robot and the participant, both groups experienced identical service tasks, processes, and sequences across all service stages. Linguistic and behavioral cues were used to shape the robot's interactional role, drawing on the master-servant and partner-based human-machine interaction frameworks (Teng et al., 2024). Participants were randomly assigned to one of four conditions and instructed to examine scenario-specific visual materials and assess their perceived level of involvement.

5.1.2. Manipulation Test

The ANOVA results from experiment 1 revealed significant differences in participants' perceptions of interaction levels across the different service contact groups [$M_{\text{Low level}} = 4.04$, $SD = 1.57$; $M_{\text{High level}} = 4.68$, $SD = 1.56$; $F(1,224) = 9.45$, $p = 0.002 < 0.05$]. The participants' perceptions of robot roles across various types of HCI also showed notable variations [M Master = 4.23, SD = 1.38; M Partner = 4.68, SD = 1.50; $F(1,224) = 5.30$, $p = 0.022 < 0.05$]. This manipulation of the service contact level and the HCI relationship in this paper was successful.

5.1.3. Main Effect

The results further demonstrated that adoption intention toward service robots was not markedly influenced by the service contact level [F (1,221) = 0.10, $p = 0.748 > 0.05$], nor by the dynamics of the HCI [F (1,221) = 0.01, $p = 0.917 > 0.05$]. The analysis results indicate a notable interaction effect between the two fundamental variables: service contact level and the relationship of HCI. This interaction continues to exert a significant influence on the consumers' adoption intention of service robots, as evidenced by [F (1,220) = 9.82, $p = 0.002<0.05$].

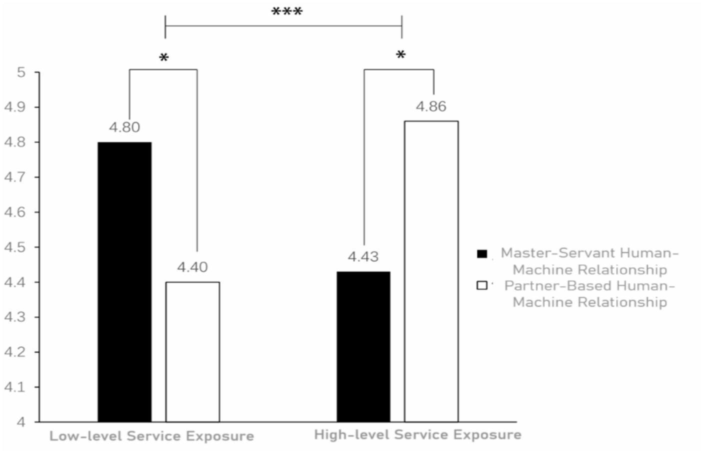


Figure 5. The influence via experiment 1 of effect of HCI modes on consumers' adoption intention toward service robots

As illustrated in Figure 5, the analytical outcomes indicate that in scenarios characterized by low-level service interaction, the establishment of a master-servant HCI framework significantly enhances consumers' adoption intention of service robots, as evidenced by the following statistics: $M_{Partner} = 4.40$, SD=1.04; $M_{Master} = 4.80$, SD = 0.98; F (1,221) = 4.53, $p = 0.034 < 0.05$. Conversely, in contexts involving high-level service interaction, the partner-based HCI model markedly increases consumers' adoption intention of service robots when compared to the master-servant dynamic, with the data reflecting: $M_{Master} = 4.43$, SD = 0.98; $M_{Partner} = 4.86$, SD = 0.94; F (1,221) = 5.40, $p = 0.021< 0.05$.

Experiment 1 uses situational imagination to manipulate the service contact level and HCI relationship. The experimental results show that the hypotheses H1, H1a and H1b in this paper are preliminarily established, and the main effect is verified. Experiment 2 will also change the material background (restaurant meal) to continue verifying the main effect and testing the mediating effects of cognitive trust and emotional trust.

5.2. 2nd Experiment: Mediation Test Based on Restaurant Service Context

5.2.1. Pretest

The objective of the pretest is to confirm the validity of the experimental material at the service contact level. In this pretest experiment, 80 valid observation samples were collected via the Credamo platform. The average age of the pretest participants was 32.5, and the gender distribution was 73.7% (59) for females and 26.3% (21) for males. The pretest experiment was designed to compare groups with a single factor and two levels for the primary variable of service exposure level (high level vs. low level). The two groups were requested to assess the extent of interaction they experienced with the service automaton "Rupert" during the supper session. The results indicated that the service robots that inquired about tastes recommended dishes, and recorded them during the ordering process had a greater degree of interaction with the subjects than those that only interacted during the food delivery process [$M_{Low} = 3.63$, $SD = 1.54$; $M_{High} = 5.75$, $SD = 1.01$; $F(1,78) = 53.02$, $p < .001$]. Consequently, the pretest corroborates the validity of the experimental materials at the service exposure level.

5.2.2. Manipulation Test

A minimal sample size of 179 persons was determined using G*power 3.1, with an effect size of 0.25, a significance threshold of 0.05, and a statistical power of 0.8. The data underwent a cleansing process using a dual quality control mechanism, including implementing attention screening questions and filtering for anomalous response times, resulting in 292 valid experimental observation questionnaires. The participant gender distribution was 28.8% (84) males and 71.2% (208) females, with a mean age of 31.09 years. In addition, the highest educational level among the participants was undergraduate (73.3%, 214 people), followed by associate degree (11.6%, 34 people).

The highest monthly income among the participants was between 3,500 and 10,000 yuan (81.8%, 147 people), followed by 10,000-20,000 yuan (26.7%, 78 people).

The results of the ANOVA test showed that there were significant differences in the perception of interaction degree among the participants in different service contact level groups [$M_{\text{Low level}} = 4.82$, $SD = 1.43$; $M_{\text{High level}} = 5.84$, $SD = 0.80$; $F(1,224) = 58.99$, $p < 0.05$]. , and there were also significant differences in the participants' perception of robot roles in different HCI groups [$M_{\text{Master}} = 3.12$, $SD = 1.87$; $M_{\text{Partner}} = 5.38$, $SD = 1.53$; $F(1,291) = 127.79$, $p < 0.05$], that is, the manipulation of service contact level and HCI relationship in this study was successful.

5.2.3. Main Effect Test

The manipulation of service contact level and the relationship between HCI in this paper proved effective. The findings indicated that the level of service contact did not exert a statistically significant influence on consumers' adoption intention of service robots [$F(1,288) = 0.402$, $p = 0.526 > 0.05$], nor did the HCI relationship impact the adoption intention of service robots [$F(1,288) = 0.001$, $p = 0.971 > 0.05$]. However, the interaction between the service contact level and the HCI relationship demonstrated a significant effect on the adoption intention of service robots [$F(1,221) = 10.993$, $p = 0.001$]. Subsequently, during the processing of control variables, the participants' novelty and familiarity with the service robot were incorporated into the analysis of the covariance model for statistical adjustment. The results of the data analysis indicated that the two fundamental variables —namely, service contact level and the HCI relationship —retained a significant interaction effect. This interaction continued to exert a substantial influence on consumers' adoption intention of service robots [$F(1,286) = 10.180$, $p = 0.002 < 0.05$], while effectively mitigating the potential interference of novelty and familiarity on the outcome variables. Figure 6 illustrates that the analysis results indicate that in low-level service interactions, the master-servant dynamic of HCI enhances consumers' adoption intention of service robots, as evidenced by the following statistics: $M_{\text{Partner}} = 5.73$, $SD = 0.94$; $M_{\text{Master}} = 6.06$, $SD = 0.62$; $F(1,288) = 5.13$, $p = 0.024$, Cohen's $d = 0.415$. In the context of advanced service interactions, the establishment of a partner-based HCI relationship, as opposed to a traditional master-servant dynamic with consumers, significantly enhances consumers' adoption intention toward service robots [M_{Master} = 5.80, SD =1.00; $M_{Partner}$ = 6.12, SD = 0.67; $F(1,288) = 5.95$, $p=0.015 < 0.05$; Cohen's d = 0.376].

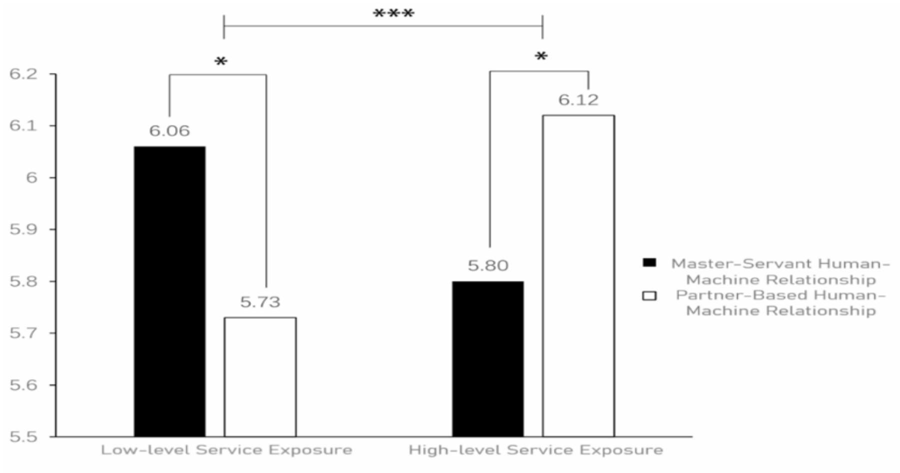
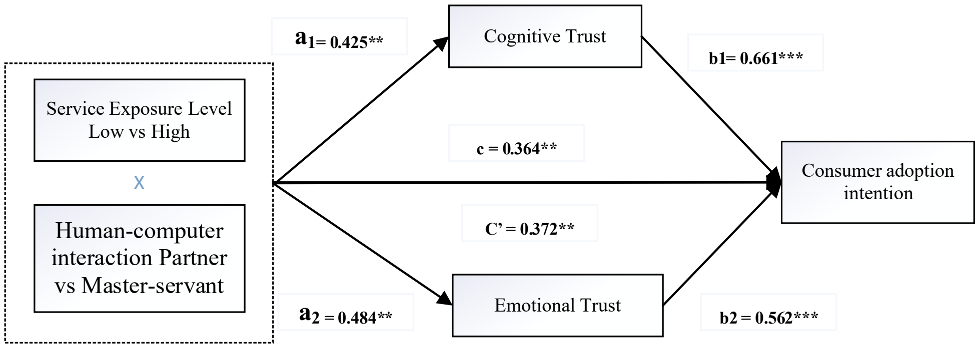


Figure 6. The influence via experiment 2 of different HCI modes on consumers' adoption intention of service robots

5.2.4. Mediating Effect

This experiment further utilizes the bootstrapping method recommended by Rockwood and Hayes (2020) to assess the mediating effect rigorously. As illustrated in Figure 7, this facilitates a comprehensive examination of the moderated mediation effect. In this analysis, the sample size was established at 5,000, with a 95% confidence interval. The variable a_1 was designated to illustrate the influence of service contact level and the interaction terms of HCI on cognitive trust. Conversely, b_1 was employed to depict the effect of cognitive trust on the adoption intention of service robots. The results, derived from bootstrapping, indicated a significant indirect mediation effect ($a_1 \times b_1 \approx 0.281$, 95% CI= [0.043,0.555]). The interaction term between service contact level and the HCI relationship had a significant effect on cognitive trust, with a quantified effect of 0.425 and a 95% confidence interval of [0.057, 0.794]. The influence of cognitive trust on consumers' adoption intention toward service robots was measured at 0.661, with a 95% confidence interval of [0.568, 0.754]. In particular, when the service contact level is minimal, the cognitive trust serves as a mediator in the relationship between HCI and the intention to adopt robots, with the confidence interval not encompassing 0 (LLCI = -0.398, ULCI = -0.020). Nevertheless, when the service contact level is elevated, cognitive trust fails to mediate the relationship between HCI and consumers' adoption intention of service robots, as evidenced by the confidence interval that includes 0 (LLCI = -0.064, ULCI = 0.263). This outcome substantiates H2a. Ultimately, the direct influence of service contact level and the relationship between HCI and intention to adopt were found to be significant, with an effect size of c = 0.364, 95% CI = [0.065, 0.662]. These results are mentioned in Figure 7.

Furthermore, a_2 denotes the influence of the interaction between service contact level and the HCI relationship on emotional trust. At the same time, B2 signifies the effect of emotional trust on consumers' adoption intention of service robots. The indirect mediating effect demonstrated significance through bootstrapping ($a_1 \times b_1 \approx 0.272$, 95% CI = 0.058 to 0.542). The impact of the service contact level and the relationship between HCI and emotional trust was measured at 0.484, with a 95% confidence interval of [0.093, 0.876]. The influence of emotional trust on the intention to adopt robots was quantified at 0.562, with a 95% confidence interval of [0.469, 0.655]. In particular, when the service contact level is diminished, the impact of the relationship between emotional trust and HCI on the intention to adopt the robot is also reduced, with the confidence interval encompassing 0 (LLCI = -0.279, ULCI = 0.055). When the service contact level is elevated, the emotional trust serves as a mediator in the relationship between HCI and the intention to adopt robots, with the confidence interval distinctly excluding 0 (LLCI = 0.029, ULCI = 0.354). This outcome substantiates H2b. Ultimately, the direct influence of service contact level and the relationship between HCI and the intention to adopt robots was found to be significant, with an effect size of c' = 0.372, 95% CI = [0.056, 0.689].



Note: * indicates p<0.05, ** indicates p<0.01, and *** indicates p<0.001

Figure 7. Bootstrapping mediation analysis

Our experimental findings consistently validate H_1, H_{1a}, and H_{1b}, indicating that consumers are more inclined to utilize service robots in servant roles under low-level service contact conditions. At the same time, they are more predisposed to engage with service robots in partner roles under high-level service contact conditions, demonstrating the robustness and generalizability of the results. In Experiment 2, it was confirmed that, under conditions of little service interaction, cognitive trust modulates the effect of the HCI connection on the intention to adopt robots. In the context of high-level service engagement, emotional trust modulates the impact of HCI on consumers' adoption intention of service robots, thereby confirming hypotheses H2a and H2b.

5.3. 3rd Experiment: Moderation based on the Shopping Guide Service Context

5.3.1. *Pretest*

Our 3rd multi-phase experimental framework comprised two initial pretests followed by a main experiment to evaluate the effects of service exposure, task difficulty, and perceptions of robot roles on user engagement and intentions to adopt inside a supermarket environment. A total of 80 valid replies were collected, with participants averaging 30.8 years of age; 80% identified as female. The results confirmed successful manipulation of service exposure [$M_{Low} = 3.28$, $SD = 1.66$; $M_{High} = 5.55$, $SD = 1.22$; $F(1,78) = 48.68$, $p < .001$]. The second pretest, which examined low and high task complexity, yielded 64 valid responses, comprising 76.6% female participants with a mean age of 31.3 years. The results indicated a significant difference in perceived complexity between conditions, with means of $M_{Low} = 4.62$ (SD = 1.19) and $M_{High} = 5.52$ (SD = 0.84), yielding an $F(1, 62) = 12.69$ and a significance level of $p < 0.01$.

5.3.2. Manipulation Procedure

A necessary sample size of 237 was established using G*Power 3.1, with an effect size of 0.25, a significance threshold of $\alpha = 0.05$, and a power of 0.8. After a comprehensive assessment of data quality, 398 valid responses were retained, comprising 69.3% female participants with a mean age of 32.24. The highest educational level among the participants was undergraduate (73.6%, 293 people), followed by postgraduate (13.1%, 52 people). The highest monthly income among the participants was between 3,500 and 10,000 yuan (52.3%, 208 people), followed by 10,000-20,000 yuan (28.1%, 112 people). Participants completed evaluations of perceived interaction, role perception, task difficulty, and consumers' adoption intention of service robots, along with demographic and covariate data (e.g., preference for Rupert).

The ANOVA revealed notable differences in participants' perceptions of interaction levels across service contact groups [M Low level = 4.82, SD = 1.43; M High level = 5.84, SD = 0.80; $F(1, 224) = 58.99$, $p < 0.05$]. Additionally, significant differences were observed in participants' perceptions of robot roles across distinct HCI categories [M Master = 3.12, SD = 1.87; M Partner = 5.38, SD = 1.53; $F(1, 291) = 127.79$, $p < .001$]. There were notable differences in how service complexity, as delivered by service robots, was perceived among participants categorized into varying task-complexity groups [M Servant = 3.12, SD = 1.87; M Partner = 5.38, SD = 1.5353; $F(1,291) = 127.79$, $p < 0.05$]. This indicates that the manipulation of the three primary variables—service contact level, HCI relationship, and task complexity—was effectively executed in this study.

5.3.3. Impact of HCI Mode on Trust

Initially, the examination focuses on the impact of the HCI mode on cognitive trust across varying levels of task complexity. Examining cognitive trust as the dependent variable revealed that the degree of service contact and HCI, influenced by task complexity, significantly affected the dynamics of cognitive trust, with $F(1,397) = 8.52$,

$p = 0.004 < 0.01$. In the context of high-complexity task conditions, notable effects of service contact level and HCI on cognitive trust interaction were observed. Specifically, within the low-level service contact group, the master-servant human-machine relationship $M_{\text{Master-servant}}=5.94$, $SD=0.10$ demonstrated a greater capacity to foster cognitive trust compared to the partner-based HCI relationship [$M_{\text{Partner}}=5.57$, $SD = 0.10$, $F(1,89) = 7.00$, $p = 0.008$, Cohen's $d = 0.429$]. In the high-level service contact group, the cognitive trust established by the partners was not significantly different from that in master-servant HCI relationships with M of 5.88, $SD = 0.10$ and 5.83 ($SD = 0.10$) and $F(1,107) = 0.15$, $p=0.699 > 0.05$, Cohen's $d = 0.052$. In the low-complexity task condition, the cognitive trust exhibited by participants in the high-level service contact group $M_{\text{Partner}} = 5.66$, $SD = 0.10$ did not significantly differ from that in the master-servant human-machine relationship $M_{\text{Master}} =5.48$, $SD = 0.10$ and $F(1,91) =1.71$, $p=0.191 > 0.05$, Cohen's $d = 0.272$; In the low-level service contact group, the cognitive trust exhibited no significant difference between the master-servant human-machine relationship [$M_{\text{Master}} = 5.65$, $SD=0.10$] and the partner human-machine relationship $M_{\text{Partner}} =5.48$, $SD=0.10$, $F(1,107) = 1.96$, $p = 0.162 > 0.05$, Cohen's $d = 0.221$.

Considering affective trust as the dependent variable, the analysis revealed that the degree of service contact and HCI significantly influenced affective trust interactions, particularly in the context of task complexity, $F(1,397) = 11.27$, $p = 0.001 < 0.01$. Specifically, within the high-level service contact group, the partner-based human-computer relationship $M_{\text{Partner}} = 5.78$, $SD = 0.11$, demonstrated a greater capacity to foster emotional trust compared to the master-servant human-machine relationship $M_{\text{Master}} =5.13$, $SD = 0.11$, $F(1,91) =17.335$, $p < 0.001$, Cohen's $d = 0.859$. In the low-level service contact group, the emotional trust exhibited by participants within the master-servant human-machine relationship did not reveal any significant differences. The data indicated a mean for the master-servant relationship at 5.60 with a standard deviation of 0.10, supported by the statistical analysis $F(1,107) = 0.12$, $p = 0.730 > 0.05$, Cohen's $d = 0.062$. In the context of high-complexity task conditions, the analysis revealed no significant difference in emotional trust when comparing the service contact level with the HCI relationship, $F(1,89) = 1.508$, $p = 0.220$. Specifically, the master-servant human-machine relationship [$M_{\text{Master-servant}}=5.73$, $SD = 0.11$, Cohen's $d = 0.204$] did not differ notably from the partner-based human-computer relationship $M_{\text{Partner}} = 5.53$, $SD = 0.11$, $p > 0.05$. In the high-level service contact group, the emotional trust exhibited by participants in the partner-based human-machine relationship [$M_{\text{Partner}}=5.77$, $SD=0.10$] was not significantly different from that in the master-servant human-machine relationship $M_{\text{Master-servant}}=5.65$, $SD=0.10$, $F(1,107) = 0.673$, $p=0.413 > 0.05$, Cohen's $d = 0.142$.

5.3.4. Moderated-Mediation Effect Test

The mediated moderation analysis was systematically executed using a bootstrap resampling approach with 5,000 iterations and a 95% confidence interval, ensuring robust statistical inference and the reliability of the estimated indirect effects(Rockwood & Hayes, 2020). The findings indicated that following the implementation of the task complexity condition, the mediating effect of cognitive trust was $b = 0.33$, $SE = 0.87$, 95% CI = [0.159, 0.501]. In contrast, the mediating effect of affective trust was $b = 0.39$, $SE = 0.78$, 95% CI = [0.237, 0.543].

Initially, regarding cognitive trust, the indirect influence of cognitive trust on individuals within the low-level service contact group proved to be significant when faced with high-complexity tasks, exhibiting an effect size of $b = -0.122$, $SE = 0.054$, 95% CI = [-0.246, -0.033]. Conversely, no indirect effect was observed for participants in the high-level service contact group ($b=0.016$, $SE=0.042$, 95%CI = [-0.060, 0.114]). In scenarios characterized by low-complexity tasks, the cognitive trust did not exhibit significance among participants in the high-level service contact group ($b=0.060$, $SE=0.058$, 95%CI = [-0.032, 0.194]), nor among those in the low-level service contact group ($b=-0.059$, $SE=0.058$, 95% CI = [-0.191, 0.040]).Second, regarding affective trust, in the context of low-complexity tasks, the indirect effect of affective trust was notably significant for participants in the high-level service contact group, as evidenced by an effect size of $b = 0.252$, $SE = 0.095$, 95% CI = [0.089, 0.462]. Conversely, there was no observable indirect effect for participants in the low-level service contact group ($b=-0.019$, $SE=0.056$, 95% CI = [-0.138, 0.087]). In the context of high-complexity tasks, affective trust did not demonstrate significance among participants in the low-level service contact group ($b=-0.075$, $SE=0.061$, 95% CI = [-0.207, 0.031]), nor did it for those in the high-level service contact group ($b=0.046$, $SE=0.056$, 95%CI= [-0.054, 0.168]).

The high-complexity task enhances cognitive trust among consumers interacting with the service robot during low-level service contact, while the low-complexity task bolsters emotional trust among consumers engaging with the companion robot during high-level service contact, thereby increasing consumers' adoption intention of service robots. Consequently, H_{3a} and H_{3b} are corroborated by data validation in the findings of Experiment 3.

6. General Discussion

This paper concludes by integrating interpersonal interaction theory and role theory within the context of HCI in the service sector. Research on traditional interpersonal interactions indicates that the formation of social connections depends on reciprocal emotional expression and empathic comprehension, while the intensity of these interactions influences the behavioral patterns of the participants (Shechtman & Horowitz, 2006). Consistent with these principles, the positive effects observed for H1a and H1b demonstrate that HCI can foster pseudo-social relationships via trust formation across both low- and high-service contact contexts, confirming that algorithmically mediated interactions can reproduce relational dynamics similar to human service encounters at varying levels of service contact. This isomorphic relationship facilitates the derivation of research perspectives and theoretical frameworks for HCI by analogously applying principles and constructs from the domain of interpersonal interaction (Alarcon et al., 2021). Our study findings reveal that service robots elicit emotional projection from consumers through algorithmic adaptation, devoid of intrinsic emotions (Liu et al., 2024; Soliman et al., 2024). Consequently, the emotional bond fostered by data-driven simulations leads consumers to develop unilateral social attachments. The varying degrees of contact intensity represent the ambiguous intersection of social cognitive boundaries, which has evolved from studies of interpersonal interactions to encompass HCI. The service contact level offers a temporal perspective, serving as a time-driven contact element that enhances role theory by introducing a dynamic viewpoint. This underscores the need for the role of service robots to be flexibly adjusted to task requirements and contact levels, rather than adhering to static presets. The clarity of the role and the intricacy of role transformation influence the alignment of consumers' perceptions, needs, and behaviors in HCI as the service contact level increases, corroborating prior research (Yoon & Lee, 2019). Moreover, social exchange theory suggests that maintaining interpersonal relationships relies on resource reciprocity, which involves an unequal exchange mechanism comparable to and relevant to HCI (Li et al., 2024). In both master-servant and partner-based HCI, customers attribute emotional significance to the actions of the service machine via subjective interpretation, therefore attaining psychological equilibrium in unequal exchanges. This paper, through H_{2a} and H_{2b}, also examines trust as the foundation of resource reciprocity, explicitly focusing on cognitive and emotional trust (Law & Scheutz, 2021). Service robots, characterized by their "tool attributes," can convey "emotional attributes" through highly anthropomorphic social role-playing during service tasks. This asymmetric exchange connection enables this article to provide a more appropriate and rigorous explanatory mechanism for examining the link between consumers' adoption intention toward service robots and variations in service contact levels. Our study findings also indicate that cognitive workload in service delivery is imperceptibly increased by the requirement for consumers to concentrate attentively on the task due to increased task complexity, particularly in scenarios of limited interaction.

In the same way, tasks of reduced complexity enable consumers to devote greater attention and energy to HCI, particularly when engagement levels are elevated. Furthermore, excess cognitive capacity encourages consumers to prioritize adaptable interactive experiences and potential emotive connections throughout the service process and adoption. This finding aligns with prior research on individual behavior conducted by (Ahn et al., 2025; Xu et al., 2020). Finally, this paper facilitates further investigation into the dynamic adaptation mechanisms of robots. Specifically, in the initial low-level contact phase, the algorithm engages the robot's "master-servant mode" to swiftly establish cognitive trust by enhancing functional performance; for instance, the hotel delivery robot adheres strictly to the designated path and minimizes superfluous interactions (such as greetings) to fulfil the efficiency expectations of low-level contact consumers. Conversely, in the high-level contact phase, the algorithm transitions the robot to "partner mode," incorporating emotional interactions (such as memory preferences and proactive suggestions) to cultivate emotional trust. Service providers or robot managers may employ reinforcement learning, such as Q-learning algorithms, to refine strategies for aligning contact levels with persona types, utilizing consumer satisfaction as a reward signal. Additionally, they can incorporate contact-level threshold detection to initiate mode switching when interactions exceed a predetermined threshold automatically.

In summary, consumers exhibit a greater consumers’ adoption intention toward service robots by activating the collaborative decision-making module, which utilizes algorithms to provide step-by-step guidance and identify user-requested keywords through natural language processing. They also adjust their behavioral expectations in real time and may even tolerate algorithmic errors to preserve the relationship, thereby achieving a balance between algorithms and consumer behaviors and establishing a sustainable model of HCI.

6.1. Theoretical Implications

This paper examines the interplay between service contact levels and HCI dynamics regarding consumers’ adoption intention of service robots, yielding several theoretical advances.

First, previous research on service robots has shown a deficiency in comprehending the impact of service contact level on customers' interactive reactions to these robots. Most of these studies (Alarcon et al., 2021; Alhaji et al., 2025; Roesler et al., 2024; Sheehan et al., 2020) have concentrated on the modalities and phases of interaction between customers and service robots, neglecting the intrinsic attributes of service contact itself. This paper posits that the logical examination of HCI can be derived from the theory of interpersonal interaction. It focuses on the varying levels of service contact, highlighting that consumers possess distinct service requirements for service robots based on their degree of interaction, which consequently influences their adoption. This paper addresses the limitations of studies on the extent of interaction with service robots, which often focus solely on direct contact. It facilitates consumer-service robot engagement and classifies service contacts by intensity to provide innovative insights into the study of service robot interaction. Examining the correlation between service contact level and human-computer interaction using experimental methods offers significant implications for theoretical development. Understanding customer responses to service robots may need more nuanced classifications beyond the standard dichotomy of anthropomorphism vs non-anthropomorphism. For this purpose, this study utilizes role theory to understand the binary contact by categorizing service interactions into high-level and low-level classifications within the partner and master-servant interaction context. Our research results also indicate that the processes of trust creation vary depending on the social role assumed by the robot and the frequency and level of interactions. Therefore, our findings provide substantial theoretical development through a comprehensive analysis that illustrates the influence of varying levels of contact on customer acceptance and role-based cues in robotic services.

Second, we defined the concept of role allocation for service robots by categorizing them into two distinct types: servant robots and master robots. In this context, previous studies (Chen et al., 2020; Guido et al., 2025; Sun et al., 2023) have mainly concentrated on specific anthropomorphic cues or distinct character traits, often leading to a fragmented understanding of the roles of service robots. Our findings highlight the critical significance of anthropomorphism and bidirectional phenomenon in shaping consumer perspectives at different contact levels. Experimental methods augment role theory about service robots, enhancing theoretical understanding and offering a more refined framework for analyzing consumer-service robot interactions in the service industry.

Finally, we determined that human-machine interaction is not a unidirectional process characterized by the progressive anthropomorphizing of service robots. The primary focus of prior research has been on the capacity of service robots to replicate human behaviors, including emotions, gestures, and language, to enhance customer acceptance (Chuah et al., 2021; Della Corte et al., 2023; Tussyadiah et al., 2020). Our findings augment the theoretical understanding of HCI by introducing the concept of social norm reconstruction. This lays a fundamental foundation for future scholarly inquiries into cognitive transfer and directs the ethical design of HCI in light of the growing societal integration with service robot technologies.

6.2. Practical Implications

This paper provides essential management insights for service organizations aiming to deploy service robots in frontline interactions and to understand their acceptance. A thorough understanding of the correlation between the operational roles of service robots and the dynamics of the service environment is crucial for developing an efficient model of human-machine collaboration (Wang & Zhan, 2024). Based on past studies (Ayyildiz et al., 2022; Reis et al., 2020), our results primarily indicate that implementing service robots in practical environments necessitates meticulous alignment between the robots' mission goals and the service operations of the enterprises. For instance, companies should use a servant-type interaction model in service interactions marked by limited contact. This strategy helps conserve service resources, optimize service procedures, and effectively address operational challenges. On the other hand, businesses must use a partner-based interaction approach for services requiring significant engagement, such as check-in processes or food ordering suggestions. This method promotes customer interaction with service robots and enables them to assist with more complex or supplemental tasks, improving service performance and overall firm performance.

Second, given the growing importance of human-machine trust, scholars argue that service providers must intentionally tailor the complexity of interactive interfaces throughout the trust-building process. In this intricate phase, the firm must perpetually refine the service algorithm by gathering data on the client's comprehensive interaction cycle. At the same time, the consumer acknowledges the accuracy of demand articulation throughout the evolving service engagement. Therefore, the current study has established a beneficial development cycle for human-machine collaboration, designed to increase consumer confidence in integrating service robotics into the service industry through an integrated trust-building model. Further, it will assist in restructuring employees' job roles and facilitate greater value co-creation in human-machine collaboration.

Finally, the analytical approach of this paper facilitates the continuous assessment and improvement of distinctive strategies for fostering trust, designed to deliver immediate practical benefits or bolster long-term product utilization. For instance, our research findings empower service providers to establish a customer lifecycle management system informed by data, aligning service contact levels and trust dimensions with commercial value objectives. In the initial stages of service engagement, service providers should focus on bolstering cognitive trust through a master-servant-machine interaction framework, particularly by evaluating job completion rates, response times, and operational effectiveness. As interactions increase, service providers may progressively incorporate partner-like characteristics to cultivate emotional trust, which can be measured through customer engagement and satisfaction metrics. Therefore, this adaptive management model presents a sustainable framework for enhancing human-robot collaboration and maximizing commercial profitability.

7. Conclusion

This paper comprehensively examines the factors that shape consumers' adoption intention toward service robots. A theoretically grounded model was developed to accomplish this objective and subsequently subjected to experimental testing and empirical validation. The results reveal that in low-level service scenarios with minimal customer interaction, the master-servant paradigm is more successful in promoting consumer adoption intentions than the partnership model. Similarly, partner-based engagement markedly increases customers' adoption intention of service robots in high-level service contexts. These findings highlight the importance of aligning the robot's functional role with the service environment to enhance customer acceptance.

Moreover, this paper affirms that both cognitive and emotional dimensions of trust play a critical mediating role in the relationship between HCI styles and consumers' intention to adopt service robots. In scenarios with minimal interaction, the adoption process is predominantly shaped by cognitive trust, which concerns consumers' evaluation of the robot's competence and effectiveness in performing tasks. On the other hand, high-contact situations foster increased emotional trust, as customers cultivate affective bonds with service robots perceived as amiable and honest companions. These results significantly contribute to the existing body of knowledge and offer practical insights for service providers by synthesizing the aspects of service contact and trust within the HCI framework.

Although this paper employed rigorous methods, certain limitations remain, offering meaningful directions for future research. First, this study recruited data from the Credamo platform and presented limited demographic diversity. The employed experimental method ensures internal validity; however, the contrived nature of online scenarios limits ecological generalizability. Since China is now the world's biggest adopter and investor in service robots, tfuture research should focus on authentic interactions through field quasi-experiments and data-driven analysis, collaborating with industry stakeholders to enhance external validity. Second, while the binary classification of HCI into servant and partner roles is grounded in established literature, it oversimplifies the increasingly complex responsibilities of service robots in healthcare, education, and domestic environments. Therefore, further refinement is necessary to precisely capture the complex social responsibilities that service robots increasingly assume. Finally, this study highlights the significance of cognitive and emotional trust; however, other psychological dimensions may also contribute to understanding consumer adoption patterns. Future research should incorporate additional mediators (such as familiarity and psychological distance) and moderators (including individual characteristics and service contexts) to create more thorough explanatory frameworks.

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