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# Customer–Robot Interaction Beyond the First Encounter: A Reciprocal Framework and Quadrant Model for Value Co-Creation

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## ABSTRACT

As service robots move from factory floors to frontline service encounters, their success increasingly depends on the quality of customer-robot interaction (CRI). Existing studies, however, remain fragmented and predominantly grounded in linear technology adoption models, offering limited insight into the dynamic and reciprocal nature of CRI over time. Addressing this gap, this systematic literature review synthesises 113 peer-reviewed articles and makes two main contributions. First, it develops a reciprocal framework that conceptualises CRI as path-dependent process in which drivers and barriers shape experiential responses, leading to attitudinal and behavioural outcomes that, in turn, recalibrate customer expectations through feedback loops. This framework advances prior one-way technology adoption models (e.g., TAM/UTAUT) by focusing on the value creation through repeated interactions in robotic service encounters. Second, the review introduces a quadrant-based model of robot-task fit structured by task complexity and service goal orientations. Extending existing robot typologies, this model specifies when particular experiential mechanism dominate and how reciprocal feedback loops vary across four robot roles: mechanical, analytical, socially interactive, and empathetic. Together, these contributions offer a holistic and contingent understanding of CRI, generating actionable insights for future research developments and for the design of effective, human-centric service robots.

## 1 | Introduction

Service robots are transforming how services are delivered, evolving from industrial automation to interactive, social roles across sectors such as healthcare, education, tourism and hospitality (Shin et al. 2025; Kuo et al. 2011; Jörling et al. 2019). Unlike virtual agents, these physical embodiments utilise anthropomorphic cues that can enhance customer's perceptions of efficiency, enjoyment and social presence during service encounters (Belanche et al. 2021). Because services are inherently dynamic—characterised by constant changes in customer expectations and real-time updates—the introduction of service robots change customer's roles from passive recipients in human-lead services to more active participants who need to learn, adapt and interact with robotic protocols. This shift raises a fundamental customer-centric question: how do customers and robots co-create value (e.g., through personalised and enjoyable interactions) or co-destroy value (e.g., via social friction, discomfort or privacy loss) over time, and why does this process lead to successful adoption in some contexts but failure in others?

Addressing this question is challenging because research on customer-robot interaction (CRI) remains fragmented. Existing studies typically focus on isolated elements, such as robot capabilities, design constraints and technical underpinnings (Gibelli et al. 2021; Mukherjee et al. 2022; Støre et al. 2022; Hung et al. 2023; Cayetano-Jimenez et al. 2024; Sun and Wang 2022), or customer expectations and behavioural responses (Gonzalez-Aguirre et al. 2021; Singh et al. 2021; Xu et al. 2023) without offering a unified theoretical structure. As a result, current research offers limited insight into how value is dynamically created or destroyed across repeated interactions. This fragmentation is further reinforced by the broader service literature's emphasis on AI and virtual agents (e.g., Lynn et al. 2024; Nguyen et al. 2025; Chong et al. 2025). While these studies advance understanding of algorithmic intelligence and conversational interfaces, they often neglect the distinctive effects of physical embodiment. Indeed, a robot's physical presence, human-like cues and socio-emotional signalling strongly shape customers' first impression and influence their perceptions of warmth, competence and authenticity, thereby affecting engagement in robotic service encounters (Law et al. 2024; Ogan 2024; Yu et al. 2025).

While recent systematic literature reviews have provided valuable depth on specific facets of CRI (e.g., Lajante et al. 2023; Zhang et al. 2024; Husain and Prentice 2025), an integrated framework that captures CRI as a dynamic and reciprocal process remains both warranted and timely (Paul et al. 2021). Most existing frameworks are grounded in a technology adoption perspective (e.g., TAM or UTAUT), and conceptualise CRI as a linear sequence from antecedents to outcomes (Zhang et al. 2024; Fu et al. 2024; Xu et al. 2023; Gonzáles-Santiago et al. 2024; Liu et al. 2023; Begum et al. 2025b; Negm 2025). While analytically useful, these models inadequately reflect the interactive nature of service encounters. Because services are intangible and inseparable from their delivery (Zeithaml et al. 1985), customer evaluations evolve throughout the interaction rather than being fixed at a single decision point, which necessitates a dynamic and reciprocal conceptualisation. Drawing on service-dominant logic (SDL) perspective (Vargo and Lusch 2016), we conceptualise the service robot as a resource integrator that facilitates value-in-use. In this view, CRI unfolds as an adaptive process of mutual learning: robots adjust based on customer inputs, while customers learn to navigate robotic capabilities to achieve service goals. These interactions are path-dependent, as past interactions continuously recalibrate expectations, perceptions and behaviours. Therefore, linear models cannot fully explain the recursive processes through which value is co-created or co-destroyed in CRI.

To addresses these gaps, this study develops a unified framework for CRI from a systematic review of 113 peer-reviewed articles. Guided by a consumer-centric logic, the review synthesises the interaction process from antecedents (e.g., robot design characteristics and customer dispositions) to experiential responses (e.g., cognitive, affective, and social experiences), and ultimately to service outcomes over time. We first introduce a reciprocal framework that synthesises key components of CRI—including drivers, barriers, customer experiences, outcomes and contextual moderators—and articulates the reciprocal relationship among them. Second, we introduce a quadrant model of robot-task fit to enhance the practical utility of this framework. Extending foundational robot typologies (Huang and Rust 2018; Wirtz et al. 2018), this model maps robot roles along two dimensions central to service encounters: task complexity (simple versus complex) and service goal orientation (functional versus socio-emotional). By doing so, it explains how and why value co-creation trajectories differ across mechanical, analytical, socially interactive, and empathetic robots.

By shifting the focus from a one-way adoption decision to an adaptive and recursive process, this study advances CRI theory and provides a diagnostic tool for service design. Understanding these dynamics is essential for improving service outcomes, strengthening customer relationships, and preventing value destruction in increasingly automated service environments. To guide the readers, Section 2 outlines the review protocol, followed by Section 3 which synthesises the literature and introduces two core contributions: the reciprocal framework and quadrant model of robot-task fit. Finally, Section 4 discusses the theoretical and managerial implications, as well as limitations and opportunities for future research.

## 2 | Methodology

The study undertakes a systematic literature review (SLR) to address the gaps in the current understanding of CRI. An SLR is a rigorous methodology for synthesising scientific knowledge by ensuring transparency, reproducibility and comprehensive coverage (Lame 2019). By following a prescribed protocol, an SLR minimises reviewer bias and enhance clarity throughout every stage of the review process (Zhang et al. 2024). To ensure methodological robustness, this study adheres to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta Analyses), which is a widely recognised standard that improve consistency and replicability in systematic literature review (Ford et al. 2023; Xu et al. 2023). The review follows a structured three-phases process illustrated in Figure 1. The first phase involves identifying relevant scholarly databases, formulating search terms, and establishing screening criteria. The second phase entails an application of eligibility rules to titles, abstracts and full texts of relevant articles. The final phase involves documenting, synthesising, and presenting the findings.

### 2.1 | Literature Search Strategy

The first step of the SLR involved determining where and how to identify relevant articles. Following Zhang et al. (2024) who suggested the use of concept-driven search blocks, we developed search terms structured around five key conceptual blocks central to CRI, including service robots, service environments, consumers, drivers and barriers, and the use and acceptance. To ensure comprehensive coverage, synonyms for each conceptual block were exhaustively identified (Table 1). Additionally, the asterisk (*) was employed to capture variations of key terms, while Boolean operators were incorporated to optimise the search strategy—an approach consistent with prior robot-related reviews (He and Zhang 2023; Lu et al. 2020; Shishehgar et al. 2018; Zhang et al. 2024).

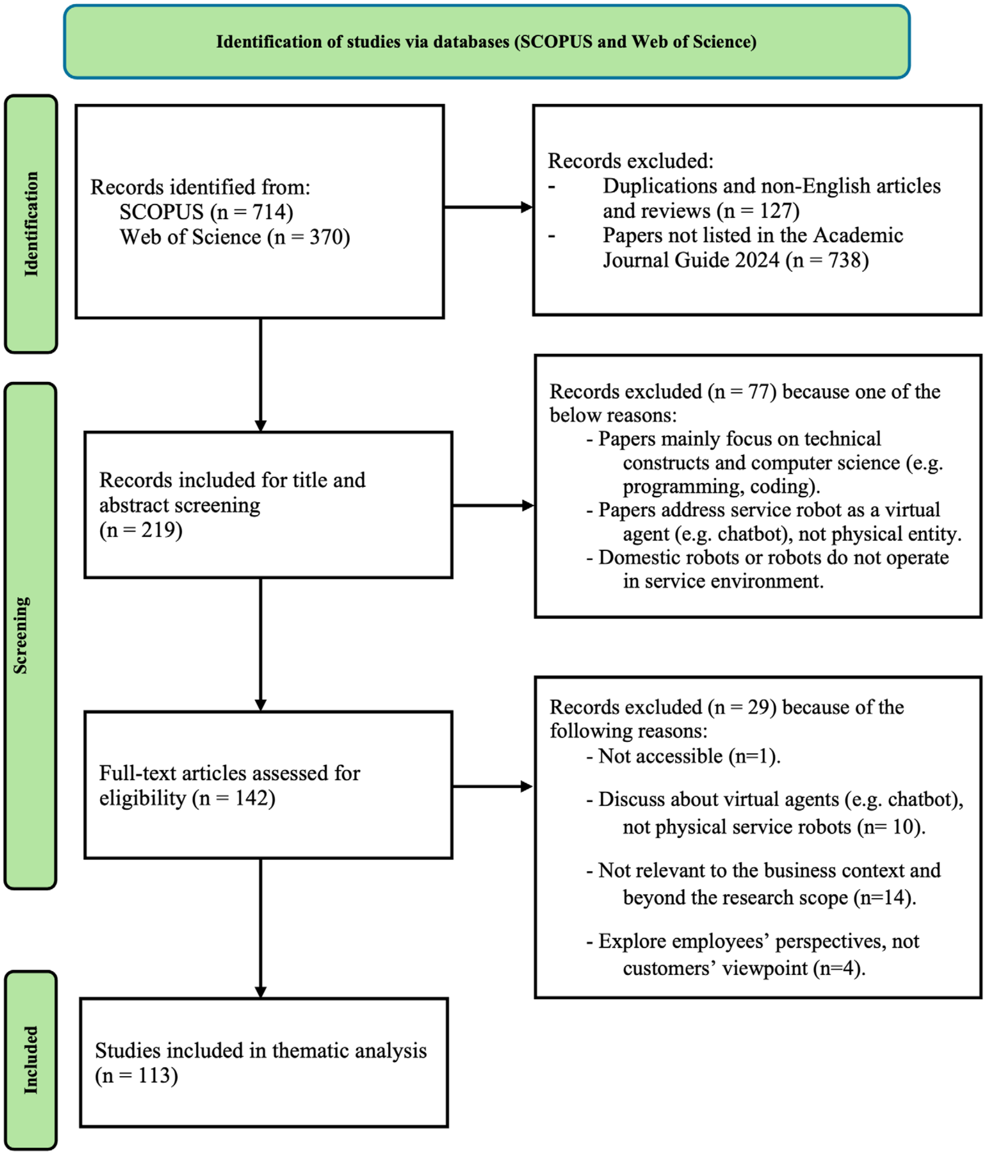


**FIGURE 1** | Articles selection procedures.

**TABLE 1** | Core concepts and keywords.

| Core concepts | Keywords |
|---|---|
| Service robot | "service robot*" OR "robot*" OR "automation" |
| Service environment | "service setting" OR "service" OR "service environment" |
| Consumers | "customer*" OR "consumer*" OR "user*" |
| Drivers and barriers | "barrier*" OR "challenge*" OR "resistan*" OR "enabler*" OR "antecedent*" OR "driver*" |
| Use and acceptance | "acceptance" OR "technology acceptance" OR "adoption" OR "technology adoption" OR "intention" OR "use and acceptance" |

The data collection centred on two major scholarly databases: Web of Science (WoS) and Scopus. These platforms were chosen because of their comprehensiveness, advanced search functionalities, and inclusion of multidisciplinary research published in AJG-ranked journals (Pranckutė 2021). Their breadth also ensures access to high-quality, peer-reviewed, open-access literature spanning technology, business, and service disciplines. The initial search was conducted using the following string: (TITLE-ABS-KEY("service robot*" OR "robot*" OR "automation") AND TITLE-ABS-KEY("service setting" OR "service" OR "service environment") AND TITLE-ABS-KEY ("customer*" OR "consumer*" OR "user*") AND TITLE-ABS-KEY ("barrier*" OR "challenge*" OR "resistan*" OR "enabler*" OR "antecedent*" OR "driver*") AND TITLE-ABS-KEY ("acceptance" OR "technology acceptance" OR "adoption" OR "technology adoption" OR "intention" OR "use and acceptance")). This search generated a total of 1084 results, with 714 records from Scopus and 370 from WoS.

### 2.2 | Inclusion Criteria and Screening Eligibilities

The screening process began with the exclusion of records based on document type, source title, and language. Regarding document type, only peer-reviewed journal articles were included while other sources (e.g., conference papers, book chapters, books, notes and editorials) were excluded due to their lack of rigorous review process or incomplete publication status. This aligns with review studies in marketing and service research, which emphasise journal articles as the most up-to-date and credible sources of knowledge (Zhang et al. 2024; Xu et al. 2023). Sources titles were then restricted to journal listed in the Academic Journal Guide (AJD) 2024, ensuring a scholarly quality and relevance for business and management perspectives (Zhang et al. 2024). While this criterion may exclude specialised publications from engineering or robotics, it is deemed appropriate given this review's focus on CRI within service and business contexts. Additionally, non-English publications were also excluded to ensure consistency and accessibility in the review process. Adhering to these criteria, 127 duplicates and 738 non-AJG articles were excluded, leaving 219 articles for further evaluation.

A title and abstract screening were subsequently conducted to isolate studies examining physical service robots interacting with customers. Consistent with our focus on embodied agents, we adopted the definition of Jörling et al. (2019, 405), who define service robots as "information technology in a physical embodiment, providing customised services by performing physical as well as nonphysical tasks with a high degree of autonomy." Based on this definition, the following criteria were applied. Firstly, only studies involved physically embodied robots interacting with customers in service environments were retained; studies on virtual agents (e.g., online chatbots) were excluded. Secondly, papers must examine customer-facing service settings, rather than personal, domestic or professional robots (e.g., warehouse robots, household vacuum robots). Finally, only studies situated within business or customer-oriented contexts were retained. Papers focusing on technical or engineering concepts (e.g., algorithm design or programming methods) were excluded. Applying these criteria resulted in the removal of 77 additional articles, leaving 142 papers for full-text screening.

In several cases, titles and abstracts did not clearly indicate study relevance. Therefore, full-text evaluation was conducted using the same criteria. An additional 29 papers were excluded at this stage due to non-retrievability (1 paper), a focus on virtual agents (10 papers), and misalignment with business and consumer-centred research (18 papers). The final dataset consisted of 113 articles (listed in the Supporting Information S1) that were retained for in-depth analysis.

## 3 | Findings

### 3.1 | Publication Trends and Descriptive Analysis

Before synthesising the reciprocal framework of CRI, we first provided a descriptive overview of the 113 reviewed articles. As shown in Figure 2, publication activity has increased sharply since 2020, signalling accelerating scholarly interest in human-robot interaction, particularly within service contexts.

Figure 3 highlights the top contributing journals in the service robot literature. Notably, *Technological Forecasting and Social Change, International Journal of Hospitality Management, Journal of Retailing and Consumer Services, Journal of Services Marketing, International Journal of Contemporary Hospitality Management, and Current Issues in Tourism* emerge as the leading publication outlets. This concentration reflects the interdisciplinary nature of CRI research, which spans technology forecasting, hospitality, marketing, and service management. Geographically (Figure 4), research output is largely concentrated in China (32 papers), the United States (23 papers), and the United Kingdom (11 papers), with growing contributions from India, South Korea, Singapore, Taiwan, and several countries

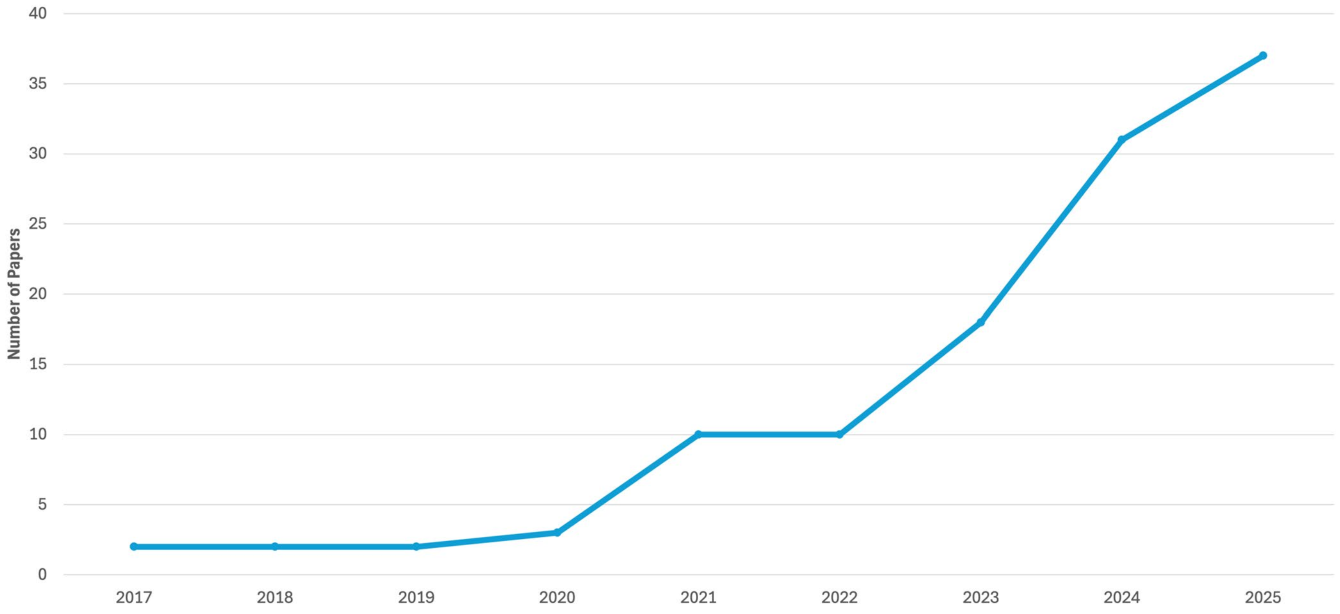


**FIGURE 2** | Distribution of publications over the years.

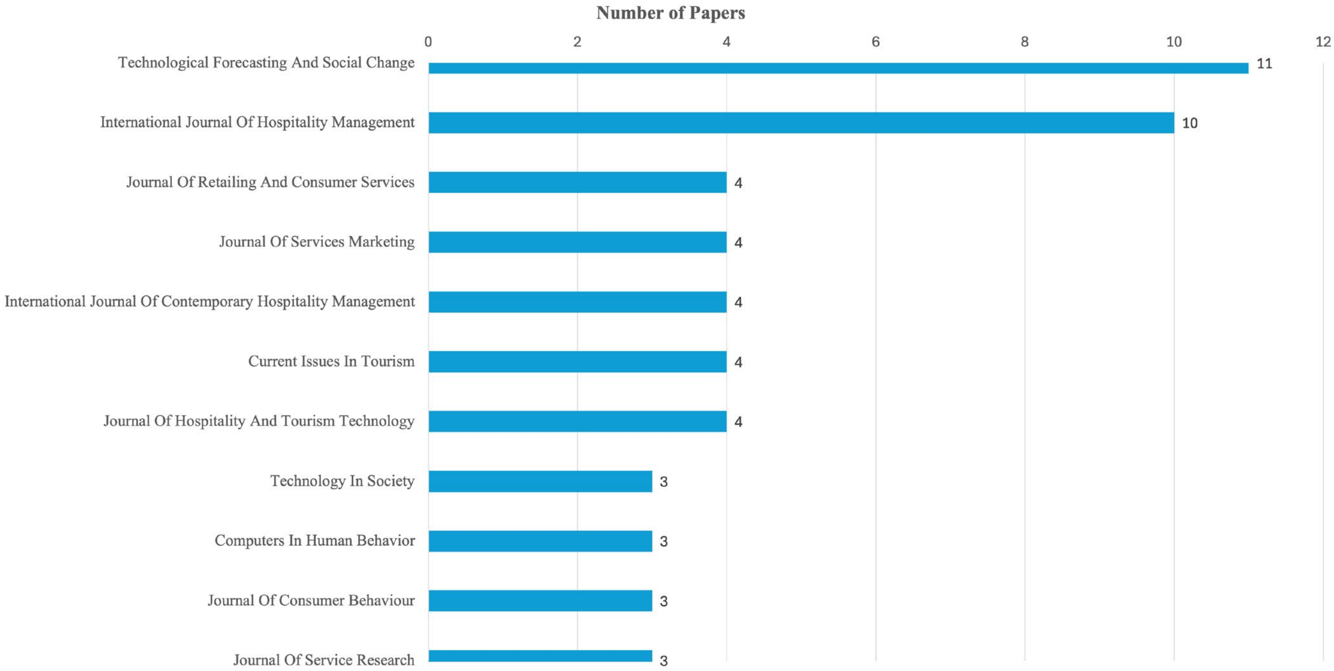


**FIGURE 3** | Top contributing journals.

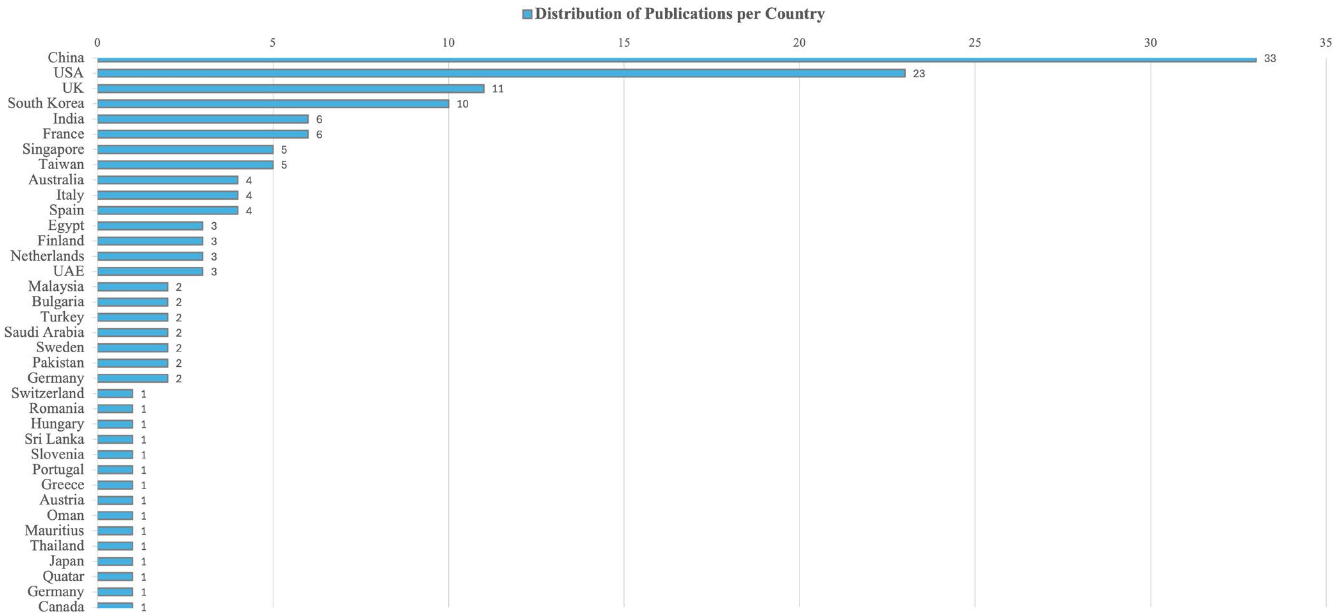


**FIGURE 4** | Distribution of publications per country.

across the Middle East and Europe. This geographical distribution highlights both the global relevance of service robotics and the uneven diffusion of research activity across regions.

In terms of research methodology (Figure 5), quantitative studies, particularly surveys and questionnaires, dominate the field with 47% of all studies. Experimental research accounts for 15%, offering contextual depth and capturing actual user behaviours under controlled conditions. Qualitative and mixed-methods studies each represent 14%, offering rich interpretive insights. Conceptual and review studies comprise the remaining 10%, reflecting a still-emerging but growing effort to theorise CRI more holistically.

### 3.2 | Key Components of Customer-Robot Interaction in Service Encounters

A service encounter is defined as “the dyadic interaction between a service recipient and a service provider” (Solomon et al. 1985), highlighting their joint influence on service differentiation, quality control and service satisfaction (Li et al. 2023). While traditionally centred on human-to-human interactions, service encounters increasingly involve robotic service providers, in which customers and robots jointly influence service experiences and outcomes (Stock and Merkle 2017; Belanche et al. 2020a, 2020b). These interactions are particularly salient in experiential and socially embedded contexts

**FIGURE 5** | The percentages of published papers using different research methods.

such as hospitality, retail, and tourism (Mettler et al. 2017; Tuomi et al. 2021; Tussyadiah et al. 2020). Importantly, robot-enabled service encounters extend beyond the focal customers to affect other stakeholders, including employees, organisations and even wider communities (Breidbach and Maglio 2016; Danaher and Gallan 2016; Mahr et al. 2025). Consequently, robotic service encounters function as dynamic nodes within an evolving service ecosystem, where value could be co-created or co-destroyed (Čaić et al. 2018).

From a value creation perspective, service robots can enhance the efficiency, operational performance and service experiences, while optimising the costs. At the same time, these encounters may also generate value destruction through diminished human contact, heightened feelings of dependence or perceived privacy loss (Broadbent et al. 2009). Such outcomes are not unilateral but reciprocal: customers and surrounding actors (e.g., employees and family members) continuously assess whether the interaction leaves them better or worse off (Čaić et al. 2018). Drawing upon this perspective, this review synthesises five interrelated components shaping CRI: (1) interaction drivers, (2) interaction barriers, (3) customer experiences, (4) attitudinal and behavioural outcomes, and (5) contextual moderators. These components are anchored in established theoretical frameworks (e.g., TAM, UTAUT, CASA) and together provide a structured account of how CRI unfolds across service contexts.

### 3.3 | Drivers of Customer-Robot Interaction

The adoption and effectiveness of service robots are influenced by a set of drivers that motivate customers to engage with robotic services. These drivers were classified into two categories (Table 2), including robot capabilities and customer dispositions.

**Robot capabilities** encompass both external and internal attributes that motivate users to interact with them. Externally, physical appearance serves as an important heuristic through which customers infer a robot's competence, trustworthiness, and role suitability (Huang et al. 2021; Blut et al. 2021). Existing taxonomies distinguish between machine-like, human-like (anthropomorphic), animal-like (zoomorphic), and ambiguous designed form (Tussyadiah et al. 2020; Liu and Xu 2023). Among these, anthropomorphic forms are consistently found to be more effective in socially embedded roles (e.g., barista, servers, shopping assistants or tour guides), where interaction quality and social cues are salient (Kim, Lee, and Kang 2023; Ruiz-Equihua et al. 2023; Fukawa et al. 2023; Wong and Wong 2024; Baltaci et al. 2024). This aligns with Anthropomorphism theory suggesting that humans naturally project social attributes onto entities that resemble themselves (Epley et al. 2007). These designs—congruent with Computers Are Social Actors (CASA) paradigm (Nass et al. 1994)—encourage users to apply social scripts to robots exhibiting human-like cues, thereby facilitating engagement and trust (Tussyadiah et al. 2020; Zhu, Jiang, et al. 2023). Beyond surface cues, internal attributes, such as autonomy (Xiao and Kumar 2021; Kim, Lee, and Kang 2023; Li and Wang 2022; Li et al. 2023), and competence (Wu, Fan, et al. 2021; Chen and Girish 2023a, 2023b) also play a critical role in sustaining interaction quality, particularly in efficiency-driven contexts. Apart from functional features, experiential attributes, such as coolness (Rasheed et al. 2024; Chen and Girish 2023a, 2023b), courtesy (Huang et al. 2021), cuteness (Huang et al. 2021; Fang et al. 2023), and uniqueness (Tuomi et al. 2021) further enhance CRI by enriching interaction quality and emotional appeal.

**Customer dispositions**, which refer to the individual characteristics, also critically shape CRI. Individual traits, such as optimism, innovativeness, openness and readiness to new experience, technological self-efficacy and faith in technology are captured by the Technology Readiness (Parasuraman 2000), which helps explain how individuals evaluate and adopt robotic services. For instance, individuals with a growth and optimistic mindset can motivate themselves to seek new experiences and drive their enthusiasms for robotic technologies (Baltaci et al. 2024; Victorino et al. 2009; Jung et al. 2023; Tariq et al. 2025; Lv et al. 2025), whereas individuals with lower openness or confidence in technology often prefer human-led services (Xiao and Kumar 2021; Chuah et al. 2021). Technological self-efficacy and trust in technology also predict acceptance, with higher technological faith associated with greater perceived reliability and goal attainment (Alam et al. 2024; Szabo and Webster 2021; Chaysang et al. 2025).

### 3.4 | Barriers of Customer-Robot Interaction

Despite the presence of strong drivers, numerous barriers constrain customer engagement with service robots. We categorised these barriers into two dimensions (Table 3): design limitations and psychological or ethical concerns.

**Design limitations** fall into three broad categories: aesthetic shortcomings, functional deficiencies, and social interaction constraints. Unattractive appearances, such as clumsy form, outdated aesthetics (Zhao et al. 2024), or rigid and repetitive movements (Wang, Zhang, et al. 2023) negatively affect first impressions and willingness to interact (Zhang et al. 2021; Fu et al. 2022). Especially, when robots appear human-like but fail to behave convincingly, expectation violations emerge and trigger the uncanny valley effect (Mori et al. 2012). Functional deficiencies further exacerbate resistance to CRI.

**TABLE 2** | Drivers of customer-robot interaction.

| Dimension | Sub-dimension | Elements | Authors | Theoretical anchor |
|---|---|---|---|---|
| Robot capabilities | Internal attributes | • Autonomy<br>• Competence<br>• Coolness<br>• Courtesy<br>• Cuteness<br>• Uniqueness | Xiao and Kumar (2021); Singh et al. (2024); Huang et al. (2021); Chen, Li, et al. (2024); Mishra et al. (2024); Kim, Lee, and Kang (2023); Kang et al. (2023); Tuomi et al. (2021); Chen and Girish (2023a) and (2023b); Wu, Fan, et al. (2021); Wong and Wong (2024); Fang et al. (2023); Baltaci et al. (2024); Li and Wang (2022); Shehawy et al. (2025); Li et al. (2023); Zubizarreta-Barrenetxea et al. (2024); Rasheed et al. (2024); Chen and Girish (2023a) and (2023b); Wong and Wong (2025b); Zhang et al. (2025) | Computers are social actors Nass et al. (1994)<br>Anthropomorphism Theory Epley et al. (2007) |
|  | External attributes | • Robot form: machine-like, human-like, animal-like. | Xiao and Kumar (2021); Blut et al. (2021); Tussyadiah et al. (2020); Liu and Xu (2023); Huang et al. (2021); Chen, Li, et al. (2024); Kim, Lee, and Kang (2023); Kang et al. (2023); Della Corte et al. (2023); Ruiz-Equihua et al. (2023); Zhu, Lin, and Liu (2023); Fukawa et al. (2023); Chuah et al. (2021); Wong and Wong (2024); Baltaci et al. (2024); Binesh et al. (2024); Van Pinxteren et al. (2019); Li and Wang (2022); Pelau et al. (2021); Shehawy et al. (2025); Barone et al. (2024); Molinillo et al. (2023); Li et al. (2023); Zubizarreta-Barrenetxea et al. (2024); Lin et al. (2020) |  |
| Customer dispositions |  | • Faith in technology<br>• Technological self-efficacy<br>• Optimism and innovativeness<br>• Openness to experience, readiness | Xiao and Kumar (2021); Tussyadiah et al. (2020); Chuah et al. (2021); Baltaci et al. (2024); Alam et al. (2024); Chaysang et al. (2025); Tariq et al. (2025) | Technology readiness Parasuraman (2000) |

Limited adaptability, inflexibility or risks of malfunction reduce perceived competence and reliability in robotic services, reinforcing preferences for human employees (Wang, Zhang, et al. 2023; Tung and Au 2018; Huang et al. 2023). Technological complexity also poses a significant barrier, especially for customers with limited digital literacy, who may perceive robotic interfaces as cognitively demanding (Rasheed et al. 2023). In addition, social interaction constraints further hinder CRI. Mis-interpretation, awkward gestures, or inappropriate responses create the gaps between expected and actual performance, consistent with Expectation Confirmed Theory (Oliver 1980), weakening relational quality and reinforce

**TABLE 3** | Barriers of customer-robot interaction.

| Dimension | Sub-dimension | Elements | Authors | Theoretical anchor |
|---|---|---|---|---|
| Design limitations | Aesthetic issues | • Lack of anthropomorphic feature<br>• Unattractive appearance<br>• Stiff kinesics | Fu et al. (2022); Wang, Zhang, et al. (2023); Zhao et al. (2024) | Anthropomorphism theory Epley et al. (2007)<br>Computers are social actors Nass et al. (1994)<br>Uncanny valley Mori et al. (2012)<br>Expectation confirmed theory Oliver (1980) |
| | Functional issues | • Concerns about robot performance<br>• Flexibility barriers<br>• Risk of malfunction<br>• Technological complexity | Wang, Zhang, et al. (2023); Huang et al. (2023); Fu et al. (2022); Nam, Dutt, et al. (2021); Rasheed et al. (2023); Mishra et al. (2024); Cho and Kwon (2025) | |
| | Social interaction issues | • Lack of warmth<br>• Low social presence | Wang, Zhang, et al. (2023); Koh and Yuen (2024); Fu et al. (2022) | |
| Psychological and ethical concerns | Technology-related concerns | • Technological anxiety<br>• Technological discomfort<br>• Technological uncertainty<br>• Job security | Baltaci et al. (2024); Kang et al. (2023); Soliman et al. (2024); Rasheed et al. (2023); Mishra et al. (2024); Cho and Kwon (2025); Wang, Zhang, et al. (2023); Han et al. (2024); Wong and Wong (2025a); Zubizarreta-Barrenetxea et al. (2024); Wang, Tang, et al. (2025); Chaysang et al. (2025); Lin and Lee (2025); Gong (2025) | Cognitive load theory Sweller (1988)<br>Social exchange theory Blau (2017) |
| | Morality and security concerns | • Privacy concerns<br>• Moral-violating behaviour | Park et al. (2021); Chuah et al. (2021); Koh and Yuen (2024); Rasheed et al. (2023); Singh et al. (2024); Söderlund (2023); Zubizarreta-Barrenetxea et al. (2024); Huang et al. (2023); Chien et al. (2025) | |

preferences for human employees (Huang et al. 2023; Koh and Yuen 2024).

Beyond design, **psychological and ethical concerns** play a critical role in shaping resistance to robotic services. Technological anxiety—feelings of apprehension when interacting with new technologies—reduces willingness to engage with service robots, particularly under conditions of uncertainty or limited experience (Wong and Wong 2025a; Rasheed et al. 2023; Han et al. 2024; Chaysang et al. 2025; Zubizarreta-Barrenetxea et al. 2024). From a cognitive load perspective (Sweller 1988), interactions that demand excessive mental effort may overwhelm users' cognitive resources, leading to stress and dysfunctional behaviours (Gong 2025). Discomfort and job insecurity associated with technology further strengthen resistance, especially in contexts where uncertainty and loss of control are salient (Baltaci et al. 2024; Flavián et al. 2022; Soliman et al. 2024). Privacy and data security concerns further inhibit adoption, particularly in contexts where robots collect or process sensitive personal information (Chien et al. 2025; Park et al. 2021; Singh et al. 2024). Consistent with Social Exchange Theory (Blau 2017), customers are less likely to accept robotic services when perceived risks outweigh anticipated benefits. Finally, moral and ethical judgements increasingly influence CRI, as customers evaluate whether robots behave in ways that align with social norms and ethical expectations. Perceived violations, such as intrusive monitoring or disrespectful behaviour, undermine trust and acceptance (Söderlund 2023; Lin and Lee 2025; Lin et al. 2025).

### 3.5 | Customer Experiences of the Interactions

While drivers and barriers shape initial engagement, customer experiences constitute the mechanisms through which CRI influences evaluations and outcomes. Consistent with prior studies (e.g., Carriedo et al. 2024; Huang et al. 2021) and the Cognitive-Affective-Social framework (Schneider et al. 2022), we categorised customers' experiences into three dimensions (Table 4): cognitive, affective and social dimensions.

**Cognitive experiences** refer to customers' mental evaluations of robotic services based on their implications and expected outcomes (Huang et al. 2024). These evaluations encompass perceived usefulness, ease of use, efficiency, intelligence and safety, which are constructs grounded in established frameworks such as TAM and UTAUT (Venkatesh et al. 2003; Davis 1989), CASA (Nass et al. 1994), Social Exchange Theory (Blau 2017). Empirical studies consistently show that higher performance expectancy and perceived intelligence foster favourable evaluations of robotic services (De

**TABLE 4** | Customer experiences of the interactions.

| Dimensions | Elements | Authors | Theoretical anchor |
|---|---|---|---|
| Cognitive experiences | • Effort expectancy<br>• Performance expectancy<br>• Perceived benefits<br>• Perceived ease of use<br>• Perceived usefulness<br>• Perceived intelligence<br>• Perceived personalisation<br>• Perceived inefficiency<br>• Perceived safety | Park et al. (2021); Chuah et al. (2021); Song, Xu, et al. (2024); Ruiz-Equihua et al. (2023); Zubizarreta-Barrenetxea et al. (2024); Chen, Li, et al. (2024); Della Corte et al. (2023); Kao and Huang (2023); Shehawy et al. (2025); Rasheed et al. (2023); Zhu, Lin, and Liu (2023); De Kervenoael et al. (2024); Binesh et al. (2024); Khaksar et al. 2024; Cho and Kwon (2025); Lin et al. (2020); Song, Gu, et al. (2024); Cabrilo et al. (2024); Wong and Wong (2024); Li et al. (2023); Li and Wang (2022); Xiao and Kumar (2021); Molinillo et al. (2023); Begum et al. (2025a); Lim et al. (2025); Bui et al. (2025) | Unified theory of acceptance and use of technology Venkatesh et al. (2003)<br>Technology acceptance model Davis (1989)<br>CASA Nass et al. (1994)<br>Social exchange theory Blau (2017)<br>Expectation confirmed theory Oliver (1980) |
| Affective experiences | • Perceived enjoyment or excitement<br>• Perceived novelty<br>• Sense of power enhancement<br>• Perceived anxiety<br>• Perceived creepiness | Azer and Alexander (2024); Huang et al. (2021); Fu et al. (2022); Kang et al. (2023); Rasheed et al. (2023); Cho and Kwon (2025); Huang et al. (2023); Cabrilo et al. (2024); Van Pinxteren et al. (2019); Liu and Xu 2023; Dang and Bertrandias (2023); Begum et al. (2025a) | Pleasure-Arousal-Dominance (PAD) framework Mehrabian (1996)<br>Uncanny Valley Mori et al. (2012) |
| Social experiences | • Perceived authenticity<br>• Perceived social presence<br>• Perceived intrusion<br>• Perceived risks or threats | Fu et al. (2022); Song et al. (2022); Tung and Law (2017); Binesh et al. (2024); Song, Gu, et al. (2024); Della Corte et al. (2023); Chen, Huang, and Miao (2024); Wang, Tang, et al. (2025); Begum et al. (2025a); Ha et al. (2025); Wang, Chan, and Gohary (2025); Yang, Lin, and Lee (2025); Li et al. (2025); Kim, Lee, Kim, et al. (2023) | Role theory Wirtz et al. (2018)<br>Social identity theory Tajfel and Turner (2004)<br>Social presence van Doorn et al. (2016) |

Kervenoael et al. 2024; Chuah et al. 2021; Binesh et al. 2024). Whereas perceived inefficient or greater effort expectancy heightens dissatisfaction and undermines adoption intention (Park et al. 2021; Chen, Li, et al. 2024; Della Corte et al. 2023; Xiao and Kumar 2021; Rasheed et al. 2023). Personalisation capabilities—typically enabled through analysis of historical consumption data—enhances cognitive appraisals by providing tailored interactions that signal being valued, thereby increasing intention to use (Khaksar et al. 2024; Bui et al. 2025). Furthermore, perceived safety is another crucial determinant of interaction quality as users' assessments of potential risks significantly influences adoption decisions (Bartneck et al. 2009; Cho and Kwon 2025; Molinillo et al. 2023). Conversely, concerns about malfunction or error, particularly in contexts where failures may cause physical harm, remain powerful barriers to acceptance (Rasheed et al. 2023).

**Affective experiences** reflect emotional responses elicited during interactions with service robots (Huang et al. 2024). Positive emotions, such as excitement, enjoyment, perceived innovativeness or perceived power enhancement, enhance customer satisfaction and foster favourable behavioural intentions (Rasheed et al. 2023; Huang et al. 2023; Cabrilo et al. 2024; Van Pinxteren et al. 2019). This aligns with the Pleasure-Arousal-Dominance (PAD) framework (Mehrabian 1996), which links pleasure and arousal to approach behaviours (Azer and Alexander 2024). Conversely, negative affects (e.g., technological anxiety and creepiness), arising when robot behaviours unpredictably and inappropriately, pose significant barriers to robot acceptance by triggering discomfort and uneasy (Fu et al. 2022; Mori et al. 2012). Novelty-seeking tendencies further amplify engagement when consumers perceive robotic services as unique or curiosity-driven experiences (Dedeoglu et al. 2018; Petrick 2002). Finally, interactions with robots can also reduce social stress relative to human encounters because robots establish predictable power dynamics that allow customers to issue commands without fear of violating social norms; thereby reinforcing perceived control and psychological ownership (Dang and Bertrandias 2023; Yang, Lee, et al. 2025).

**Social experiences** reflect the extent to which service robots meet social and relational expectations, including key dimensions such as perceived authenticity, social presence, intrusiveness, and perceived risks (Chong et al. 2025; Wirtz et al. 2018; Yang, Lin, and Lee 2025). Authenticity has emerged as a core

**TABLE 5** | The Outcome of customer-robot interaction.

| Dimensions | Elements | Authors | Theoretical anchor |
|---|---|---|---|
| Attitudinal level | • Satisfaction<br>• Trust<br>• Intention to use and acceptance | (Blut et al. (2021); Borghi and Mariani (2024); Tussyadiah et al. (2020); Han et al. (2024); Mishra et al. (2024); Tuomi et al. (2021); Zhu, Lin, and Liu (2023); Singh et al. (2024); Chen, Li, et al. (2024); Kim, Lee, and Kang (2023); Kang et al. (2023); Della Corte et al. (2023); Soliman et al. (2024); Dang and Bertrandias (2023); Park et al. (2021); Khaksar et al. (2024); Huang et al. (2021); Fu et al. (2022); Rasheed et al. (2023); Cho and Kwon (2025); Chen and Girish (2023a) and (2023b); Roy et al. (2024); Cabrilo et al. (2024); Pelau et al. (2021); Song, Xu, et al. (2024); Huang et al. (2023); Quinones et al. (2024); Chuah et al. (2021); Koh and Yuen (2024); Wong and Wong (2024); Liu et al. (2022); Baltaci et al. (2024); Van Pinxteren et al. (2019); Li and Wang (2022); Shehawy et al. (2025); Wang, Zhang, et al. (2023); Binesh et al. (2024); Molinillo et al. (2023); Li et al. (2023); Chen, Huang, and Miao (2024); Chuah et al. (2022); Goel et al. (2022); Zubizarreta-Barrenetxea et al. (2024); Lin et al. (2020); Rasheed et al. (2024); Wang, Chan, and Gohary (2025)) | Theory of reasoned action Fishbein and Ajzen (1977)<br>Technology acceptance model Davis (1989)<br>Unified theory of acceptance and use of technology Venkatesh et al. (2003) |
| Behavioural level | • Repeated purchases<br>• Engagement<br>• Word-of-mouth or referrals<br>• Approach<br>• Objection/rejection | Liu and Xu (2023); Huang et al. (2021); Chen and Girish (2023a) and (2023b); Song et al. (2022); Ruiz-Equihua et al. (2023); Cheng (2025); Wong and Wong (2024); Fang et al. (2023); De Kervenoael et al. (2024); Quinones et al. (2024); Guo et al. (2022); Wong and Wong (2025a); Lin et al. (2020); Rasheed et al. (2024); Goel et al. (2022); Chen and Girish (2023a) and (2023b); Lv et al. (2025) | |

value in service contexts: interactions perceived as genuine strengthen brand impressions and stimulate positive responses (Song et al. 2022; Bae 2021). Equally important, social presence simulation strengthens engagement and satisfaction by creating the impression of a meaningful social entity, even in the absence of genuine human agency (van Doorn et al. 2016; Binesh et al. 2024). However, social experience is not uniformly positive. Robots can be perceived as intrusive or a threat to freedom when their highly attentive service disrupts desired solitude or immersion, particularly in contexts where customers value autonomy or privacy (Wong and Wong 2025a; Čaić et al. 2018; Ha et al. 2025). Furthermore, perceived social risks and identity threats—grounded in Social Identity Theory (Tajfel and Turner 2004)—further shape customer responses towards service robots. Concerns about unauthorized access to biometric or behavioural data stored in cloud systems amplify fears of identity theft and surveillance (Tussyadiah et al. 2020; Chen, Huang, and Miao 2024). Existential threats, such as job displacement and erosion of human uniqueness, further intensify resistance (Song, Xu, et al. 2024; Della Corte et al. 2023; Kim, Lee, Kim, et al. 2023; Li et al. 2025).

### 3.6 | The Outcomes of Customer-Robot Interaction

The ultimate measure of success in CRI lies in the outcomes that emerge from these encounters, guiding evaluation of current deployments and future design improvements. In line with Xu et al. (2023), we classified the outcome into two categories (Table 5): attitudinal and behavioural level.

**Attitudinal** responses refer to internal psychological states (e.g., satisfaction, trust and acceptance intentions) that shape how consumers anticipate acting (Eagly and Chaiken 1995). Satisfaction emerges when service robots meet or exceed customer expectations, generating pleasure from the interaction (Borghi and Mariani 2024; Wang, Chan, and Gohary 2025; Chen and Girish 2023a, 2023b; Huang et al. 2021). Trust also

**TABLE 6** | Contextual factors in the customer-robot interaction.

| Dimensions | Elements | Authors | Theoretical anchor |
|---|---|---|---|
| Service-related factors | • Service contexts<br>• Task complexity<br>• Brand positioning<br>• Facilitating conditions | Xiao and Kumar (2021); Roy et al. (2024); Quinones et al. (2024); Bala et al. (2023); Blut et al. (2021); Liu and Xu (2023); Tuomi et al. (2021); Xu et al. (2025); Lin et al. (2025) | Unified theory of acceptance and use of technology Venkatesh et al. (2003)<br>Hofsted's Cultural Dimensions Hofstede and Bond (1984) |
| User-related factors | Demographics: age, gender, income and education | Han et al. (2024); Mishra et al. (2024); Bala et al. (2023); Jászberényi et al. (2024); Song, Gu, et al. (2024); Goel et al. (2022); Zubizarreta-Barrenetxea et al. (2024); Mandal et al. (2025); Wong and Wong (2025c) | |
| Cultural-related factors | • Social influence<br>• Cultural norms | Shehawy et al. (2025); Cho and Kwon (2025); Mishra et al. (2024); Chen, Huang, and Miao (2024); Della Corte et al. (2023); Ruiz-Equihua et al. (2023); Quinones et al. (2024); Guo et al. (2022); Wong and Wong (2024); Zubizarreta-Barrenetxea et al. (2024); Alam et al. (2024); Rasheed et al. (2024); Lin et al. (2020); Galdolage (2022) | |

plays a pivotal role in mitigating perceived uncertainty associated with autonomous agents. Indeed, studies show that it acts as a relational catalyst that enables customers to rely on service robots despite technological opacity and unpredictability (Della Corte et al. 2023; Binesh et al. 2024; Park et al. 2021; Roy et al. 2024). Furthermore, service robots' acceptance intention—widely examined through the Technology Acceptance Model (Davis 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003)—is also an important attitudinal responses that predict the actual usage behaviours.

**Behavioural** responses represent observable actions arising from customer attitudes and experiences, illustrating what customers actually do in practise (Fishbein and Ajzen 1977). These include approach or avoidance behaviours, repeat usage, word-of-mouth (WOM) and engagement. Positive experiences encourage customers to approach and interact more frequently with service robots (e.g., initiating conversations, exploring features) and revisit service settings, whereas negative experiences foster rejection and avoidance due to unmet expectations (Ruiz-Equihua et al. 2023; Wu, Fan, et al. 2021; Ha et al. 2025). Recent literature also suggests that ethical behaviours can also be fostered with the adoption of humanoid service robots because individuals perceive that their actions are continuously being monitored during the service usage (Deng et al. 2025). Beyond usage behaviours, word-of-mouth (WoM)—informal, interpersonal communication about a brand or service (Guo et al. 2022)—also serves as a critical behavioural outcome of CRI because it reduces uncertainty for prospective customers and is perceived as more credible than firm-generated communication (Quinones et al. 2024; Cheng 2025). However, WoM exerts a dual effect: positive WoM accelerates adoption, whereas negative WoM amplifies resistance (Wong and Wong 2024; Goel et al. 2022; Chen and Girish 2023a, 2023b). Finally, engagement, which is conceptualised as active participation in brand-related interactions, further strengthens relational bonds and fosters enduring customer-robot relationships (Hollebeek 2011; Fang et al. 2023).

### 3.7 | The Role of Contextual Factors in Customer-Robot Interaction

The effectiveness of CRI is not uniform across contexts and individuals but rather influenced by contextual factors that moderate relationships among interaction stimuli, customer experiences, and service outcomes. We grouped these moderators into three dimensions (Table 6): service-related, user-related, and culture-related factors.

**Service-related factors** include service contexts, task complexity, brand positioning and the facilitating conditions. Hedonic contexts (e.g., hospitality and tourism) emphasise affective and social experiences, making anthropomorphic and interactive robots more effective compared to utilitarian contexts (e.g., retail and transportation), which mainly prioritise efficiency, reliability and predictability (Liu and Xu 2023; Chitturi et al. 2008; Xu et al. 2025). Task criticality and complexity further condition suitability: rule-based and routine tasks (e.g., welcoming guest or giving directions) align well with simple automation, focusing more on the stability and efficiency of robotic services.

Whereas non-routine and sensitive tasks (e.g., serving and handling complaints) often relate to social and emotional experience, which could require human intervention to maintain service quality (Tuomi et al. 2021). Brand positioning also moderates acceptance, as premium services (e.g., fine dining) often may favour human interaction to elevate exclusivity and personalisation, whereas low-involvement settings (e.g., quick-service restaurants) benefit from robotic automation (Roy et al. 2024; Xiao and Kumar 2021). Additionally, literature also highlighted the importance of firms' strategies in fostering adoption. These are often viewed as facilitating conditions (e.g., clear guidance, staff assistance, and robust infrastructure), which reduce uncertainty and enhance perceived ease of use (Bala et al. 2023; Chi et al. 2021; Quinones et al. 2024).

**User-related factors** encompass demographics such as age, gender, income, and educational background. Empirical evidence suggests that men and younger consumers tend to show greater interest in advanced technologies and are more willing to spend more on such services, reflecting higher technological curiosity and digital familiarity. By contrast, women and older consumers often exhibit higher risk aversion and perceive new technologies as greater complexity (Jászberényi et al. 2024; Song, Gu, et al. 2024; Mandal et al. 2025; Bala et al. 2023; Golbabaei et al. 2020). While research has not established a definitive trend regarding income levels, some studies suggest that higher-income individuals are less likely to use service robots, whereas those in lower-income groups tend to either avoid or be early adopters (Bala et al. 2023). Lastly, acceptance of service robots is found to be positively correlated with educational level: higher educational profiles are consistently associated with stronger acceptance, likely reflecting greater technological competence (Jászberényi et al. 2024).

**Social and cultural factors**—mainly underpinned by Hofstede's culture dimensions (Hofstede and Bond 1984) and UTAUT (Venkatesh et al. 2003)—further shape consumer attitudes and behaviours towards robotic services. Cultural orientation influences perceptions of trust and appropriateness in robotic services. For instance, collectivist cultures tend to exhibit higher trust in technology and greater acceptance of automation compared to individualist cultures (Lee et al. 2013; Shehawy et al. 2025). In cultures emphasising warmth and human touch, robots may be perceived as impersonal, reducing satisfaction (Cho and Kwon 2025). Social influence, which reflects the extent to which individuals perceive the importance of when others expect them to use a technology (Venkatesh et al. 2003), also strongly predicts adoption, as individuals often rely on social cues and normative expectations when evaluating emerging technologies (Della Corte et al. 2023; Quinones et al. 2024; Galdolage 2022).

Taken together, the literature portrays CRI as a multi-layered process, where drivers and barriers shape cognitive, affective, and social experiences, which in turn lead to attitudinal and behavioural outcomes under various contextual conditions. However, existing studies often conceptualize these relationships as linear, overlooking their reciprocal and dynamic nature. Addressing this limitation, the following section develops a framework that integrates these components into a reciprocal relationship.

### 3.8 | The Reciprocal Framework

Service contexts are inherently dynamic. Beyond the classic characteristics of services, such as intangibility, inseparability, heterogeneity, and perishability (Zeithaml et al. 1985), contemporary service theories also emphasise customer journey and the evolution of value across interconnected touchpoints (Lemon and Verhoef 2016; Vargo and Lusch 2016). Consistent with service-dominant logic, value emerges and evolves through continuous interaction and mutual adjustment rather than isolated outcomes (Vargo and Lusch 2016). Accordingly, we conceptualise CRI as a reciprocal and path-dependent process (Figure 6), where enablers, barriers, experiential responses and service outcomes form a dynamic cycle rather than a linear sequence as implied in prior works (Zhang et al. 2024; Fu et al. 2024; Xu et al. 2023; Gonzáles-Santiago et al. 2024; Liu et al. 2023).

The forward pathway explains how robot-related drivers, barriers, and customer dispositions shape customer experiences, which in turn influence the interaction outcomes at attitudinal and behavioural levels. Specifically, robot-related drivers (e.g., competence, autonomy, courtesy and anthropomorphic form) and user-related dispositions (e.g., optimism, technological self-efficacy, and openness to experience) tend to improve the cognitive appraisals (e.g., perceived usefulness, ease of use, perceived intelligence), affective responses (e.g., enjoyment, arousal, reduced anxiety), and social experiences (e.g., authenticity, social presence). Conversely, barriers (e.g., complexity, inflexibility, malfunction risk or privacy concerns) undermine these experiences, reducing satisfaction, trust and engagement (Fu et al. 2022; Huang et al. 2021; Rasheed et al. 2023; Della Corte et al. 2023). Contextual moderators re-weigh these relationships. For example, in high-stakes contexts, such as medical diagnostics or financial recommendations, expectations of competence and interpretability dominate the interactions. Whereas expectations of enjoyment, warmth and social presence are more influential in pleasure-driven settings, such as hospitality and tourism (Chitturi et al. 2008; Wirtz et al. 2018). However, a purely forward-looking model treats outcomes as endpoints. In practise, these outcomes serve as inputs for future interactions, creating a series of feedback loops across encounters.

Firstly, a positive outcome at first encounter recalibrates motivations and expectations in subsequent interactions. For instance, high satisfaction can reinforce existing drivers (e.g., faith in technology, perceived competence of similar robots) and reduce perceived effort and risk, making customers more tolerant of minor aesthetic flaws. Conversely, a negative outcome can erode the initial optimism and amplify aversion, increasing cognitive load and priming avoidance (Gong 2025). This is especially critical for service failure and recovery. Consider a hotel check-in scenario: if a robot fails to scan a passport (a functional outcome failure), the customer perception of robot's competence (a driver) immediately declines. Consequently, in the next encounter, the customer approaches with pre-existing impression of incompetence (barrier) and becoming hyper-sensitive to even minor subsequent delays or errors. Meta-analytic evidence suggests that while recovering efforts can restore immediate satisfaction, they rarely return approach intentions to pre-failure levels in service encounters (De Matos et al. 2007; Liu and Wang 2025;

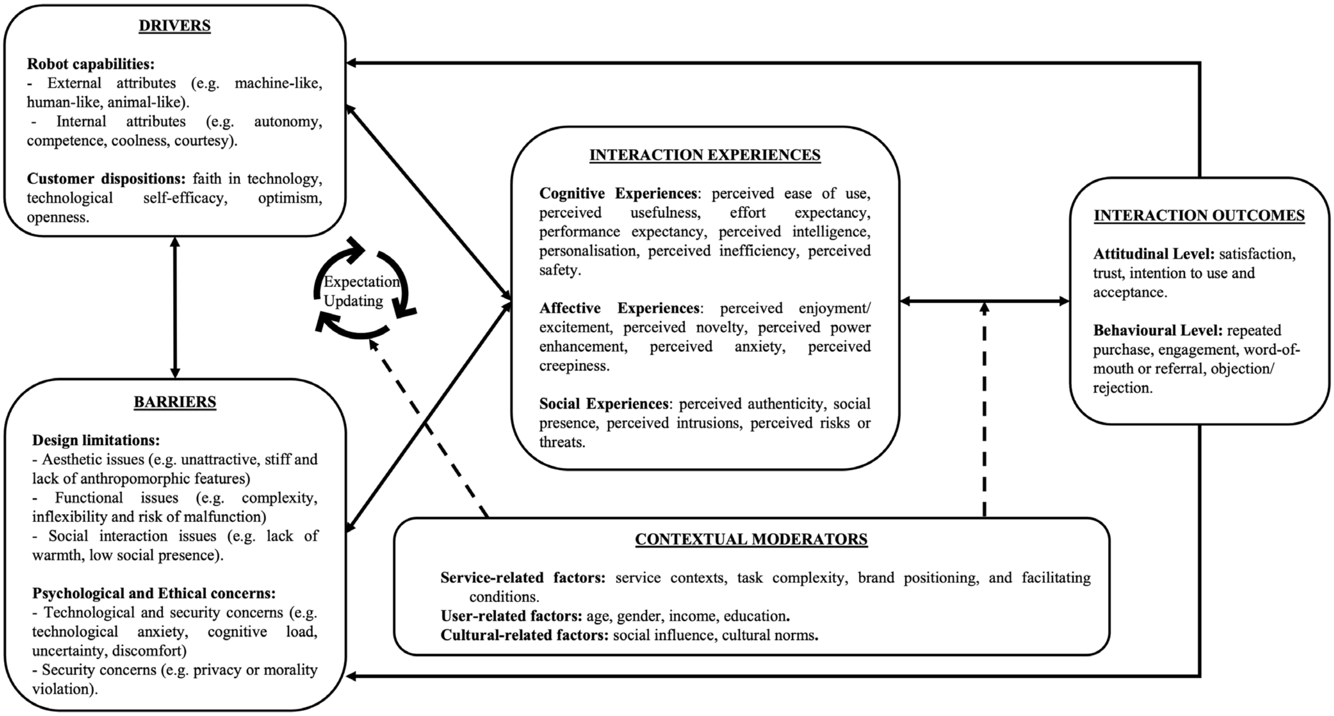


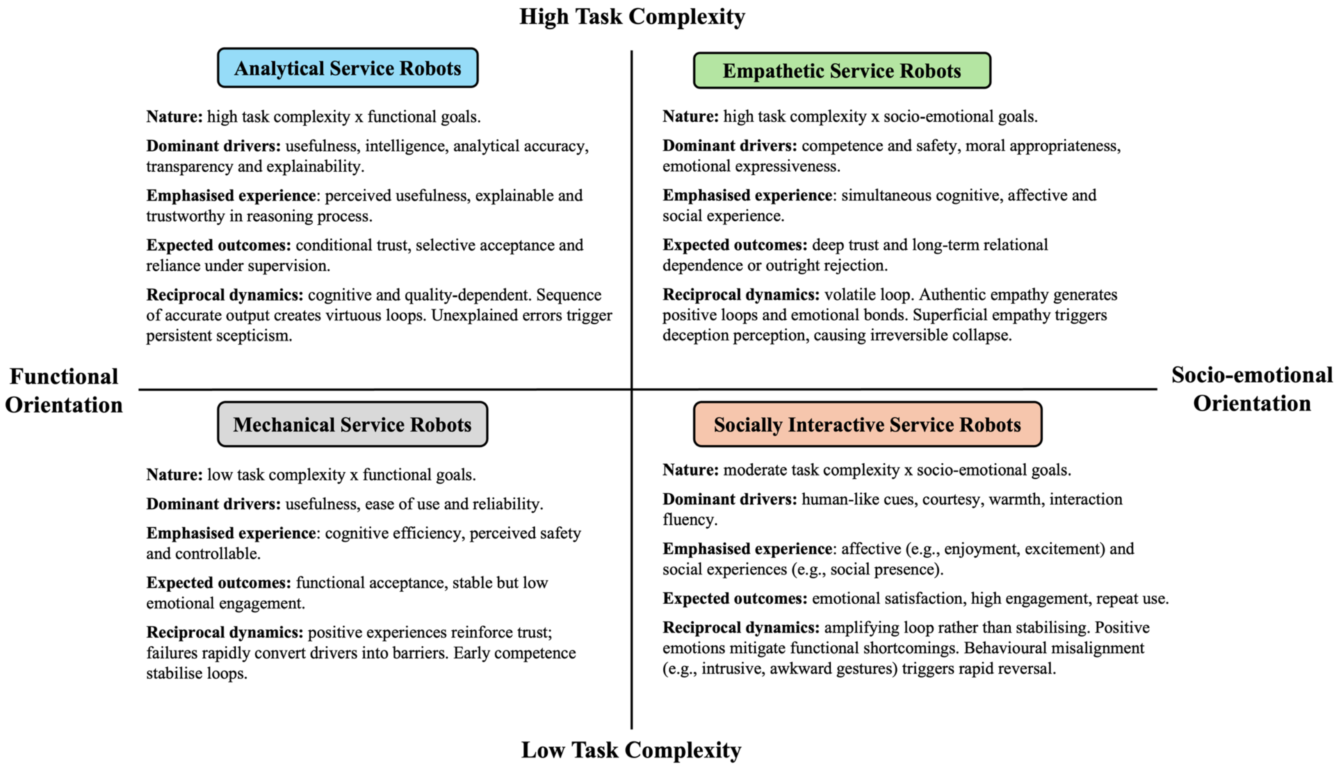
**FIGURE 6** | A reciprocal framework of customer-robot interaction.

Shin et al. 2025). This is particularly salient in robotic services because customers often attribute robotic failures to the brand itself, whereas human failures are often attributed to the individual staff member in the first place (Belanche et al. 2020a, 2020b; Pavone et al. 2023; Shin et al. 2025). As robots are viewed as direct brand extension, early experience and feedback loops become the architecture of customer long-term relationships.

Secondly, the framework also proposes the interplay between drivers, barriers and experiential responses as an "expectation updating" loop, which is represented by the circular structure. Evidence indicates that when a robot successfully mimics human-like behaviours over repeated encounters, it reinforces dispositional drivers (e.g., competence and intelligence), fosters the perceived usefulness and mitigates initial barriers such as lack of warmth or low social presence (Rasheed et al. 2023; Huang et al. 2021). Conversely, recurring malfunctions or systemic inflexibility can erode favourable experiences (e.g., usefulness and enjoyment), effectively transforming positive drivers (e.g., optimism, faith in technology) into barriers, such as technological uncertainty and anxiety.

Thirdly, we posit that outcomes do not only recalibrate future antecedents but also retrospectively reshape how prior interactions are remembered. For instance, high satisfaction (outcome) could make customers recall the cheerful aspects more vividly (affective experience), whereas dissatisfaction or frustration could intensify impressions of inefficiency (cognitive experience). Thus, CRI is a continuous process of narrative construction, where the final outcome colours the perceived quality of the preceding journeys. Because outcomes reshape how prior experiences are recalled, this reciprocity suggests the two-sided adaptation, where both parties continuously adjust to maintain the value co-creation. Service providers refine scripts and escalation rules based on outcome patterns, while robots algorithmically adjust behaviours to user signals and interaction outcomes (Chau et al. 2025). However, adaptation creates a potential vulnerability by concerns about manipulation or data exploitation. Privacy transparency and user control function as calibrators—consistent with the service trilemma of efficiency, personalisation and privacy (Phillips et al. 2023)—could help mitigate these concerns and maintain trust within the service ecosystem. For example, when personalisation is transparent and controllable, customers would attribute it to genuine service improvement rather than data exploitation, which maintains the coherence required for stable feedback loops. Thus, privacy safeguards ensure that adaptation is interpreted as responsive rather than manipulative (Martin et al. 2017).

Finally, the strength and direction of these feedback processes are contingent on identifiable boundary conditions. For example, in routine-based contexts, where performance and efficiency are paramount, early demonstrations of competence and interpretability establish positive performance expectations that buffer later minor glitches. Customers interpret failures as exceptions rather than signals of robot limitations. In these settings, affective cues can enrich the experience but cannot replace technical accuracy. By contrast, in socio-emotional encounters, the expressions of warmth, authenticity and social presence can build rapport that increases tolerance for occasional failures. Additionally, user dispositions (e.g., technology readiness and cultural norms) also shape the loop intensity at an individual level. For example, high uncertainty avoidance amplifies perceived risk after failures and slows recovery, whereas high readiness accelerates learning and reduces technological anxiety (Reimann et al. 2008; Sunny et al. 2019).



**Analytical Service Robots**

**Nature:** high task complexity x functional goals.

**Dominant drivers:** usefulness, intelligence, analytical accuracy, transparency and explainability.

**Emphasised experience**: perceived usefulness, explainable and trustworthy in reasoning process.

**Expected outcomes:** conditional trust, selective acceptance and reliance under supervision.

**Reciprocal dynamics:** cognitive and quality-dependent. Sequence of accurate output creates virtuous loops. Unexplained errors trigger persistent scepticism.

**Empathetic Service Robots**

**Nature:** high task complexity x socio-emotional goals.

**Dominant drivers:** competence and safety, moral appropriateness, emotional expressiveness.

**Emphasised experience**: simultaneous cognitive, affective and social experience.

**Expected outcomes:** deep trust and long-term relational dependence or outright rejection.

**Reciprocal dynamics:** volatile loop. Authentic empathy generates positive loops and emotional bonds. Superficial empathy triggers deception perception, causing irreversible collapse.

**Mechanical Service Robots**

**Nature:** low task complexity x functional goals.

**Dominant drivers:** usefulness, ease of use and reliability.

**Emphasised experience**: cognitive efficiency, perceived safety and controllable.

**Expected outcomes:** functional acceptance, stable but low emotional engagement.

**Reciprocal dynamics:** positive experiences reinforce trust; failures rapidly convert drivers into barriers. Early competence stabilise loops.

**Socially Interactive Service Robots**

**Nature:** moderate task complexity x socio-emotional goals.

**Dominant drivers:** human-like cues, courtesy, warmth, interaction fluency.

**Emphasised experience**: affective (e.g., enjoyment, excitement) and social experiences (e.g., social presence).

**Expected outcomes:** emotional satisfaction, high engagement, repeat use.

**Reciprocal dynamics:** amplifying loop rather than stabilising. Positive emotions mitigate functional shortcomings. Behavioural misalignment (e.g., intrusive, awkward gestures) triggers rapid reversal.

**FIGURE 7** | A quadrant-based model of robot-task fit.

## 3.9 | A Quadrant-Based Model of Robot-Task Fit

While Figure 6 conceptualises CRI as a reciprocal, path-dependent process, it remains relatively broad regarding the conditions under which experiential mechanisms dominate. Existing robot typologies (e.g., Huang and Rust 2018; Wirtz et al. 2018) classify robots primarily by intelligence levels or operating environments, implicitly assuming that greater intelligence universally enhances service outcomes. However, this feature-centric perspective overlooks a critical contingency: customer acceptance depends not only on absolute capability, but also on the alignment between task demands, service orientations, and customer expectations.

To address this gap, we propose a quadrant-based model (Figure 7) that is consistent with Task-Technology Fit (TTF) theory (Goodhue and Thompson 1995). The quadrant shifts the analytical lens from absolute capabilities to goal alignment, recognising that acceptance depends on correspondence between task demands assigned to robots and the service goal orientation. Specifically, we operationalise this theoretical congruence along two primary dimensions: (1) task complexity, and (2) service goal orientation. The vertical axis represents **task complexity**, which capture the structural and cognitive demands of a service interaction, including the number of task components, required resources, and the dynamic interaction between the task and its performer (Liu and Li 2012). It ranges from low-complexity, predictable, and rule-based tasks to high-complexity interactions requiring judgement, contextual interpretation, and adaptive decision-making. The horizontal axis represents **service goal orientations**, ranging from functional goals (e.g., speed, accuracy, cost control) to socio-emotional engagement, such as warmth, authenticity, and relational quality (Chen et al. 2025; Wang, Yan, and Wang 2023). This dimension reflects core distinctions in service research where instrumental versus experiential goals systematically reweigh cognitive and social appraisals (Vargo and Lusch 2016; Chitturi et al. 2008; Brakus et al. 2009).

The intersection of these axes yields four ideal types of service robots: mechanical, analytical, socially interactive, and empathetic. These quadrants align broadly with prior typologies but extend them by shifting the lens from asking "what the robots can do" to "what customers need the robot to be" within a specific consumption context. This model is theoretically congruent with literature on frontline service robots that differentiates capability demands from role expectations (Brakus et al. 2009; Chitturi et al. 2008). More importantly, while Figures 6 and 7 operate at different analytical levels, they are fundamentally interdependent and complementary. The reciprocal relationship of CRI (Figure 6) functions as the "engine", describing how interaction unfolds through feedback loops. The quadrants (Figure 7), on the other hand, function as the "map", identifying which contexts determine which mechanisms in the "engine" become salient and how sensitive the reciprocal loops are to disruption.

### 3.9.1 | Mechanical Service Robots (*Low Task Complexity* × *Functional Goal Orientation*)

Mechanical tasks are repetitive and routine-based activities, requiring minimal creativity or cognitive effort. Examples include self-service technologies in retail and hospitality (Fan et al. 2016; Chau et al. 2025) and autonomous transportation systems such as Birmingham Airport's Air-Rail Link (BBC News 2022). The widespread adoption of such robots offers multiple benefits, including reduced congestion, lower emissions, and improved efficiency (Quinones et al. 2024; Yoganathan and Osburg 2024; Dong et al. 2019; Schwing et al. 2025). In this quadrant, dominate drivers are primarily functional, central on reliability, efficiency and ease of use and safety, which are consistent with technology acceptance and automation research (Wirtz et al. 2018; Tussyadiah et al. 2020). Barriers related to rigid architectures, technical inflexibility and malfunction risks undermine trust and intensify automation anxiety (Fu et al. 2022). Correspondingly, cognitive experiences dominate customer evaluations. Users assess whether robots perform accurately, reduces effort and ensure safety. While these interactions involve customer resource integration (e.g., functional learning), they remain primarily within the realm of value facilitation rather because customers prioritise task completion over relational engagement, effectively limiting the potential for deeper co-creation (Grönroos and Voima 2013).

Within a reciprocal framework, positive cognitive experiences reinforce antecedents (e.g., technological trust) and reduce effort expectancy and anxiety. However, failures (e.g., breakdowns or delays) can break the loop immediately because they are often interpreted as systemic incompetence rather than situational errors (Chen, Li, et al. 2024; Wong and Wong 2025a; Soliman et al. 2024). This rapidly converts drivers into barriers, leading to avoidance and rejection. Accordingly, interaction design should prioritise early competence proof, transparency, and interpretability. Clear onboarding demonstrations, visible safeguards and escalation pathways help anchor trust and stabilise the reciprocal loop. Although privacy concerns are secondary in mechanical contexts, they becomes salient when sensor data are stored or integrated across service touchpoints, requiring explicit communication of data-handling boundaries to maintain long-term acceptance (Xie and Lei 2022; Song, Xu, et al. 2024; Khaksar et al. 2024).

### 3.9.2 | Analytical Service Robots (*High Task Complexity × Functional Goal Orientation*)

Analytical service robots extend utilitarian service delivery into high-complexity domains with non-routine cognitive demands, such as financial advising (Belanche et al. 2019; Flavián et al. 2022; Goswami et al. 2025), medical diagnostics or intelligent logistics (Strubelt 2024). While functional goals remain central, dominant drivers shift from basic efficiency towards perceived intelligence, analytical accuracy, transparency, and controllability (Wu, Nix, et al. 2021; Li and Wang 2022; Xiao and Kumar 2021). In this quadrant, cognitive experiences remain paramount but are qualitatively different from those in mechanical contexts. Customers evaluate not only whether the robot performs tasks, but whether its reasoning processes appear explainable and trustworthy (Rasheed et al. 2023; Bartneck et al. 2009; Tussyadiah et al. 2020). For instance, in high-stake domains (e.g., healthcare or finance), a reliance on outputs that the user cannot verify creates a sense of uncertainty. Without a clear explanation, customers may feel a loss of agency, reducing their long-term trust in the system (Singh et al. 2024; Fu et al. 2022). Thus, expected outcomes in these encounters include conditional trust, reliance under supervision, and selective acceptance rather than unconditional adoption.

The reciprocal dynamics in this quadrant are primarily cognitive and quality-dependent. Sequences of accurate and well-explained outputs create virtuous loops that build trust and reduce cognitive effort in subsequent interactions. Whereas unclear decisions or unexplained errors undermine core drivers such as competence and accountability, often triggering persistent skepticism or disengagement. The evolving nature is tied to the robot's learning capability: as it learns and improves, this can gradually increase user perceptions of intelligence and reliability. While affective or social cues provide reassurance, they offer limited value unless they enhance interpretability or signal human oversight (Wirtz et al. 2018). Thus, managing reciprocal loops here requires balancing intelligence with transparency rather than increasing social expressiveness.

### 3.9.3 | Socially Interactive Service Robots (*Moderate Task Complexity × Socio-Emotional Goal Orientation*)

Socially interactive robots operate in contexts where service goals prioritise engagement, enjoyment, and relational quality, while task complexity remains relatively moderate. Typical applications include robotic receptionists and servers (Cakar and Aykol 2021; Nam, Eskander, and Choo 2021; Çeltek 2024; Zhang et al. 2022), and tour guides (Wong and Wong 2024; Parvez et al. 2024; Amelia et al. 2022). Contextual understanding and responsiveness are the key to distinguish interactive robots from their analytical counterparts because robot's primary goal is to foster relational engagement through activities such as greeting, guiding and answering queries (Huang et al. 2024; Cabrilo et al. 2024). In this quadrant, dominant drivers extend beyond competence to include perceived warmth, courtesy and novelty (Huang et al. 2024; Wong and Wong 2024). Human-like cues can further invite the perception of warmth, enjoyment and authenticity (Blut et al. 2021; Huang et al. 2021; Rasheed et al. 2023). However, the same cues can heighten sensitivity to misalignment: rigid behaviour, mistimed responses or poor emotional recognition can evoke discomfort, or perceived intrusion (Fu et al. 2022; Zhang et al. 2021; Koh and Yuen 2024). Customer evaluations are shaped primarily by affective and social experiences, such as enjoyment, authenticity, and social presence. Functional performance remains necessary but is insufficient on its own to drive acceptance.

The reciprocal loops at this level are amplifying rather than stabilising. Positive affective experiences (e.g., a warm, engaging interaction) can mitigate minor functional shortcomings, reinforcing perceptions of friendliness and competence. However, behavioural misalignment (e.g., awkward timing, inappropriate responses or intrusiveness) can quickly reverse these loops. In such cases, social cues that initially acted as drivers become sources of discomfort or creepiness. This explains why socially interactive robots often succeed in light-touch experiential settings (e.g., restaurant and hotel) but struggle in emotionally sensitive or highly personalised environments (e.g., hospitals, rehabilitations, and care homes). Sustaining reciprocal loops here depends on adaptive communication and social calibration rather than solely technical sophistication (Mingotto et al. 2021).

### 3.9.4 | Empathetic Service Robots (*High Task Complexity* × *Socio-Emotional Goal Orientation*)

Empathetic service robots represent the most demanding contexts, combining high task complexity with strongly relational and emotional expectations. These roles require the sophisticated ability to recognise, interpret, and respond appropriately to human emotions, with applications in healthcare, caregiving, rehabilitation and companionship (Mishra et al. 2024; Mettler et al. 2017; Dang and Bertrandias 2025; Iglesias et al. 2021). Robots (e.g., Pearl, Care-O-bot, and Paro) equipped with face and voice recognition, gesture detection, tactile sensing, and AI-driven emotional responsiveness to facilitate diagnostic support, rehabilitation assistance, and well-being improvement, can help address workforce gaps and improve outcomes (Cantone et al. 2023; Dang and Bertrandias 2025). In this quadrant, the primary drivers of adoption are robot's functional competence, safety and emotional expressiveness. Customer evaluations in this space draw simultaneously on cognitive (e.g., perceived competence), affective and social experiences such as perceive enjoyment, empathy, authenticity, and moral appropriateness (Huang et al. 2021; McLean et al. 2021; Fong et al. 2003). While successful interactions foster deep trust, and long-term reliance, the barriers (e.g., privacy concerns, moral unease, and authenticity doubts) are equally potent. Misuses in this quadrant often trigger perceptions of emotional exploitation or manipulation (Bae 2021; Mende et al. 2019; Van Maris et al. 2020).

Reciprocal dynamics in this quadrant are volatile because the experiential influences stretch among cognitive, affective, and social appraisals. Perceived authentic empathy can catalyse positive loops, strengthening trust and emotional bonds over time. This in turn reinforces drivers (e.g., perceived warmth, courtesy) and mitigates barriers (e.g., moral unease). Conversely, superficial or misaligned displays of empathy or emotion may risk shifting the interaction from value co-creation to value co-destruction. Critically, negative loops in this quadrant tend to be irreversible; the margin for error is significantly lower than in transactional service encounters. Therefore, this quadrant represents both the greatest promise and the greatest risk, underscoring the need for ethical safeguards, human oversight, and careful calibration of emotional expressiveness.

### 3.9.5 | Cross-Quadrant Insights

Taken together, this robot-task fit model—consistent with Task-Technology Fit and service orientation literature—clarifies how the same robot attributes can produce divergent outcomes depending on task complexity and service goal orientation. Functional contexts hinge on cognitive efficiency and stabilising loops, whereas socio-emotional contexts amplify affective and relational mechanisms. As task complexity increases, reciprocal loops become more context dependent and less forgiving of failure. By integrating task–technology fit with service goal orientation, the model advances existing typologies from static categorisation towards a dynamic understanding of when, why, and how reciprocal CRI processes succeed or fail across service contexts.

# 4 | General Discussion

## 4.1 | Theoretical Contributions

Building on the interaction process logic articulated in the review, this paper contributes to CRI literature in three key ways. First, we reframed CRI as a holistic process flow that capture the experience of CRI from interaction stimuli (e.g., robot's human-like cues or users' tech-savviness), through multidimensional experiential responses (cognitive, affective and social) to the downstream service outcomes (e.g., attitudinal and behavioural outcomes). Critically, distinguishing among these experiential channels is functionally essential because it clarifies not only what matters in CRI, but also when and why particular experiences become salient. This perspective provides a more integrated account of how CRI unfolds over time.

Second, the paper formalises a reciprocal framework (Figure 6) that explains how interaction outcomes continuously reshape future evaluations. Extending TAM/UTAUT-style models (Zhang et al. 2024; Fu et al. 2024; Xu et al. 2023; Gonzáles-Santiago et al. 2024; Liu et al. 2023), we theorised CRI not as a one-shot adoption decision, but as an evolving, path-dependent process governed by feedback loops. Positive outcomes reinforce drivers and reduce barriers in subsequent interactions, whereas negative outcomes erode optimism and trigger avoidance. Importantly, the shows that interaction quality emerges from on-going interplay between drivers, barriers and experiential responses (circle labelled "Expectation updating"), rather than from single design elements. Outcomes not only update motivations for future interaction, but also retrospectively reshape memory of past experiences: satisfaction amplifies positive recall, while frustration magnifies impression of inefficiency, making evaluation dynamic rather than static. These feedback effects are particularly consequential in robotic services, where failures are often attributed to the firm rather than individual employees. This could intensify recovery challenges and amplify reputational damage (De Matos et al. 2007; Ruiz-Equihua et al. 2023; Khaksar et al. 2024). The strength and direction of feedback loop are also contingent on boundary conditions (e.g., service context, task structure, user dispositions and socio-cultural factors), which are foundational to understanding why identical mechanism produce different outcomes across service settings.

Third, the paper also advances robot typologies through a model of robot-task fit (Figure 7). Rather than defining robots by their functional capabilities (e.g., what robot can do), we shift the analytical lens to normative expectations (e.g., what the robot is expected to be) within a given service encounter. We developed the quadrant of robot-task fit across two dimensions: task complexity (routine → non routine) and service goal orientation (functional/efficiency → socio emotional/relational). This intersection yields four quadrants: mechanical, analytical, socially interactive, empathetic. Each quadrant specifies the dominant experiential channel predicts how feedback loops propagate. In utilitarian contexts, cognitive experiences (e.g., perceived usefulness and efficient) dominate, and service robots are expected to demonstrate intelligence and technically proficiency. Because the dominant outcome is functional utility, visual or design limitations pose minimal barriers to acceptance. Early demonstrations of competence stabilise the relationship, creating robust feedback loops where minor errors are easily forgiven as technical glitches. Conversely, in socio-relational contexts, affective and social experiences (e.g., perceived enjoyment, uniqueness and social presence) are paramount, and service robots are expected to convey courtesy, warmth or relational presence alongside task execution. In such settings, design flaws (e.g., rigid and mechanic behaviours, low social presence or authenticity) become significant obstacles to acceptance. The expected outcomes shift from mere utility to relational trust and emotional attachment. Consequently, service failures often trigger irreversible resistance. Customers interpret these failures through a moral or social lens, perceiving them as signs of inauthentic or manipulative intent rather than technical limitation. This explains why the same recovery strategy succeeds in some contexts but fails in others, which is not because the recovery tactic differs, but because customers evaluate it through entirely different experiential lens (De Matos et al. 2007; Phillips et al. 2023; Chitturi et al. 2008).

### 4.2 | Managerial Implications

This study translates the reciprocal CRI framework (Figure 6) and the robot-task fit model (Figure 7) into actionable guidance for service owners, technology developers and policymakers. Firstly, manager should treat customer-robot interactions as evolving experiences rather than isolated service encounters. Figure 6 demonstrates that customer responses operate as reciprocal loops in which early outcomes (e.g., trust, satisfaction or discomfort) shape expectations and tolerance in subsequent encounters. Service providers should treat initial deployment phases as trust-building stages, which prioritises predictability, transparency, and error prevention. Investments in onboarding, clear explanations of robot capabilities, and visible recovery mechanisms are particularly effective. Positive early positive experiences increase tolerance for minor future glitches, whereas negative firsthand encounters can trigger persistent anxiety and avoidance unless actively countered through recovery and reassurance (Choi et al. 2021; De Kervenoael et al. 2024).

Secondly, successful service robot deployment depends on aligning robot capabilities with task complexity and service goal orientation. As illustrated in Figure 7, customer evaluations depend on the alignment between robot capabilities, task complexity and service goal orientation. Thus, service managers can use the robot-task fit model as a practical deployment diagnostic. For instance, mechanical and analytical robots are best suited to efficiency-oriented and cognitively demanding tasks (e.g., self-checkout, autonomous delivery or financial advising), where efficiency, accuracy, and explainability sustain trust (De Kervenoael et al. 2024; Cho and Kwon 2025). In contrast, socially interactive and empathetic robots should be reserved for roles with socio-emotional goals (e.g., hospitality servers, healthcare assistants), where expressive consistency and behavioural appropriateness matter more than technical sophistication alone. Over-deploying human-like cues in utilitarian contexts, or overstating empathy in sensitive roles would risk expectation violations and rapid trust erosion (Choi et al. 2023; Kim, Lee, and Kang 2023; Cantone et al. 2023; Zhang et al. 2022).

Thirdly, service providers should segment customers based on technological readiness and culturally shaped dispositions. Figure 6 highlights that customer dispositions and cultural contexts influence how CRI is interpreted and carried forward into future encounters. Prior research shows that acceptance of service robots is positively associated with technological familiarity and confidence, whereas low readiness amplifies perceived risk and effort during interaction (Parasuraman 2000; Baltaci et al. 2024). Importantly, readiness is not purely an individual trait but is also socially and culturally shaped. For example, collectivist cultures tend to exhibit greater trust in automation and greater openness to robotic services in line with broader societal movements, whereas individualistic cultures that prioritise human touch and interpersonal contact may apply stricter evaluative standards even when functional performance is met (Cho and Kwon 2025; Shehawy et al. 2025; Lee et al. 2013). Rather than pursuing uniform rollout strategies, service providers should tailor deployment approaches to culturally shaped readiness profiles.

Finally, ethical and governance safeguards must be embedded as visible features of the interaction rather than treated as background compliance mechanisms. The negative experiences identified in Figure 6, including privacy concerns, perceived deception or manipulation, and loss of control, together with the contextual sensitivities illustrated in Figure 7, indicate that ethical design directly shapes customer experience. To mitigate these risks, service providers should move beyond post-assurance practises and integrate trust stabilisers into the user journey (Phillips et al. 2023; Tussyadiah et al. 2020; Song, Xu, et al. 2024). Clearly communicating what data are collected, how personalisation algorithms operate, and when human override applies can reassure customers (Chuah et al. 2021; Park et al. 2021). Such safeguards are particularly critical in social and empathetic contexts, where emotional engagement and data capture frequently intersect. Practises such as auditability, explainability, and privacy-by-design can transform ethical requirements into reciprocal interaction loops that stabilise trust through the service encounter (Phillips et al. 2023; Tussyadiah et al. 2020; Song, Xu, et al. 2024).

### 4.3 | Future Research Avenues

#### 4.3.1 | Empirical Validation and Refinement of the Reciprocal Framework

Future research should empirically test the proposed reciprocal framework (Figure 6) through longitudinal studies that track customer interactions with service robots over time. Methods such as experience sampling, panel surveys, and repeated interviews can capture how drivers, barriers, experiences, and outcomes evolve across encounters. Particular attention should be paid to the strength, speed, and triggers of feedback loops. For example, repeated positive affective experiences with a socially interactive robot may build trust differently from trust built through reliable performance in mechanical roles. Scholars should also examine how contextual moderators (e.g., cultural values, urgency of service needs) reshape these dynamics. In high-uncertainty cultures, for example, predictable robot functionality may be valued more than social engagement, fundamentally altering feedback processes. Example research questions include:

- To what extent do longitudinal patterns of customer experiences validate the proposed reciprocal framework for CRI?
- What contextual factors (e.g., cultural values, urgency of service need) moderate the direction and intensity of feedback loops in CRI?

#### 4.3.2 | Service Robot Design and Customer Emotional Ambivalence

Figure 6 highlights the affective duality of CRI, where positive emotions (e.g., enjoyment, excitement) co-exist with negative ones (e.g., anxiety and creepiness). This suggests that specific robotic attributes, such as anthropomorphic cues, act as double-edged swords. While these attributes activate social scripts that convey warmth and social presence, they simultaneously trigger discomfort when social cues appear imperfect or misaligned. This friction induces emotional ambivalence, which is defined as the concurrent experience of positive and negative emotions towards the same stimulus (Ashforth et al. 2014; Yao et al. 2025). Future research should examine the boundary conditions where this ambivalence either resolves through user familiarity and cognitive flexibility or escalates into service rejection. Example research questions include:

- Through what cognitive pathways do robots' social cues evoke emotional ambivalence, and how does this state influence interaction outcomes?
- Under what conditions does repeated exposure to emotionally expressive service robots attenuate versus amplify customer emotional ambivalence?

#### 4.3.3 | Exploring Nuances Within the Robot-Task Fit Quadrant Model

The robot-task fit quadrant model (Figure 7) opens avenue for examining how reciprocal dynamics vary across service contexts. For mechanical and analytical roles, studies should manipulate reliability, perceived safety, and explanatory transparency to identify thresholds at which single malfunctions produce persistent avoidance and trust. For empathetic and socially interactive robots, research should explore trade-offs among warmth, authenticity, and intrusiveness, particularly in relation to uncanny valley effects and over-promising human-like empathy. Additionally, future work should examine "transition zones" or hybrid roles in which robots combine analytical capabilities with emotional expressiveness. As AI increasingly blurs the boundary between task execution and social engagement, understanding how customers navigate these hybrid interactions and how multiple experiential dimensions jointly shape feedback loops is a critical frontier for CRI research. Example research questions include:

- How do reliability and perceived safety thresholds affect customer responses in mechanical and analytical robot roles?
- What trade-offs among warmth, authenticity, and intrusiveness shape customer responses to socially interactive robots?
- How do customers evaluate hybrid robots that combine analytical and emotional capabilities?

#### 4.3.4 | Cross-Cultural and Demographic Moderators

Future research should further contextualise CRI by examining how cultural orientations shape the relative importance of cognitive, affective, and social mechanisms. Cross-cultural comparisons can test whether uncertainty avoidance, collectivism–individualism, and power distance systematically recalibrate the roles of competence, warmth, and authenticity in reciprocal dynamics (Lee et al. 2013). Moreover, CRI is inherently multi-actor, involving customers, frontline employees, and organisations. Mixed-method studies integrating these perspectives can better capture the value co-creation process, including how employees adapt roles, how organisations recalibrate scripts and governance, and how customers interpret these changes over time (Breidbach and Maglio 2016; Xu et al. 2023). Example research questions include:

- How do customer, employee, and organisational perspectives jointly shape co-creation and value destruction dynamics in CRI?
- What roles do age, technological readiness, and digital literacy play in moderating adoption and recovery processes?
- How do cultural factors (e.g., uncertainty avoidance, power distance, collectivism–individualism) influence the relative importance of cognitive versus affective mechanisms in CRI?

### 4.4 | Limitations

This study is not without any limitations. First, it exclusively relied on Web of Science and Scopus, complemented by the AJG 2024 criterion to ensure quality and consistency. However, this focus may have excluded relevant contributions from other reputable databases (e.g., *IEEE Xplore, Google Scholar, and EBSCO*), and non-AJG journals where embodied interaction is often explored (e.g., International Journal of Social Robotics, Smart Health, IEEE Transactions on Learning Technologies, and International Journal of Advanced Robotic Systems). This boundary was intentional to maintain disciplinary coherence within service and marketing, though future reviews could expand beyond AJG to capture more interdisciplinary insights. Second, the review adopted Jörling et al. (2019, 405)'s definition of service robots as physically embodied entities in service interactions, ensuring conceptual clarity for hospitality, retail and healthcare. Broader definitions (e.g., Wirtz et al. 2018) including virtual agents were excluded, limiting applicability to digitally automated sectors such as logistics and finance services. Future research could incorporate both physical and virtual forms to reflect the evolving human-AI service landscape. Finally, the synthesis centred on the customer perspective, excluding employees or organisational views despite CRI's multi-actor nature (Breidbach and Maglio 2016; Xu et al. 2023; Mahr et al. 2025).

## Conflicts of Interest

The authors declare no conflicts of interest.

## Data Availability Statement

The list of reviewed articles supporting this study is available as Supporting Information in the online version of this article.

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## Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** ijcs70208-sup-0001-List of reviewed articles.docx.