
# Determinants of Customer Acceptance in AI-Powered Conversational Agents: A Systematic Literature Review and Research Agenda


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# Determinants of Customer Acceptance in AI-Powered Conversational Agents: A Systematic Literature Review and Research Agenda

As conversational AI agents (CAIAs) become embedded in customer–firm interactions, the theoretical models employed to account for their acceptance increasingly appear inappropriate. This systematic literature review synthesizes 58 empirical studies (2018–2025) and exposes a core tension: established frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) rest on assumptions of instrumentally rational users evaluating stable system attributes, yet CAIAs are adaptive, probabilistic, and socially responsive in ways that render those assumptions problematic. The resulting mismatch, we argue, is responsible for contradictory empirical findings, particularly at the intersection of trust, anthropomorphism, and perceived risk. Where rationalist models fall short, the Computers as Social Actors (CASA) paradigm proves more apt at capturing relational dynamics, though it too offers only a partial account. By distinguishing between utilitarian and relational agent types and between high-stakes and low-stakes decision contexts, the review uncovers boundary conditions that earlier syntheses have left unexamined. Drawing on consumer decision-making, value co-creation, and relationship management scholarship, we develop a marketing-centred research agenda comprising five theoretically grounded directions. Managerial guidance is offered for CAIA design attuned to distinct phases of the customer journey.

Keywords: conversational AI agents, technology acceptance, consumer decision-making, systematic literature review, artificial intelligence



## 1. Introduction

The increasing prominence of conversational agents (CA) driven by artificial intelligence (AI) has fundamentally reshaped human–technology interactions. These systems, deployed across financial services (Zhu et al., 2024), healthcare (Wutz et al., 2023), tourism (Pillai and Sivathanu, 2020), and e-commerce (Sidlauskiene et al., 2023), engage with users through text-based or voice-based communication to respond to inquiries and fulfil user needs. Unlike traditional rule-based systems, conversational artificial intelligence agents (CAIAs) leverage advanced machine learning models and dialogue management frameworks that adapt to user inputs, learn from past interactions, and anticipate future needs (Adam et al., 2021; Mariani et al., 2023). CAIA's adaptive learning and more complex reasoning differentiate them from earlier systems, enabling sophisticated, context-sensitive interactions that evolve over time (Følstad et al., 2019). Consequently, as CAIA adoption grows, understanding its acceptance is crucial, with determinants extending beyond conventional factors (Mariani et al., 2023).

Yet the theoretical vocabulary mobilized to explain CAIA acceptance has, in important respects, not kept pace with the technology it seeks to capture. TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) were conceived for a generation of static information systems whose perceived attributes, be it usefulness or ease of use, could reasonably be treated as stable across encounters. CAIAs, however, defy this assumption. They learn from exchanges, recalibrate their outputs, and operate under conditions of irreducible uncertainty; neither end-users nor system designers can fully anticipate how a given interaction will unfold (Chandra et al., 2022; Ling et al., 2023). A foundational tension follows. If a CAIA's perceived usefulness shifts between one conversation and the next because the system itself has materially changed, the static measurement logic on which TAM depends ceases to hold. And when users begin to anthropomorphize a CAIA, attributing social norms and expectations to its behaviour (Nass et al., 1994; Adam et al., 2021), the instrumentally rational decision-maker that UTAUT presupposes gives way to a socially responsive actor for whom acceptance hinges on relational, not merely functional, considerations.

The rationale for this review extends beyond the absence of a prior systematic synthesis focused explicitly on CAIA acceptance. More importantly, a substantial body of empirical research has developed on the basis of theoretical frameworks that were not designed to accommodate the adaptive, probabilistic, and socially responsive characteristics of contemporary AI systems. This mismatch has contributed to recurring inconsistencies in findings related to trust, perceived risk, and anthropomorphism. A meaningful synthesis must therefore move beyond a descriptive inventory of constructs and contexts. It must instead identify where established models lose explanatory precision, clarify the mechanisms underlying these shortcomings, and articulate how the theoretical architecture of the field should evolve to support cumulative knowledge development.

This SLR focuses solely on AI-powered, customer-facing, text-based CAIAs, excluding traditional rule-based systems and voice-based interfaces. Following Tranfield, Denyer, and Smart (2003), this narrow scope enables a precise examination of CAIA's unique capabilities. By adhering to these focal points, our study addresses two research questions:

RQ1: What theoretical tensions and boundary conditions emerge when established acceptance frameworks are applied to adaptive CAIAs, and to what extent are these tensions and boundary conditions contingent upon agent type and decision context?

RQ2: Where and why do traditional acceptance models (TAM/UTAUT) systematically fail to explain consumer interaction with learning, probabilistic systems, and what alternative or integrative theoretical mechanisms - drawing on social response theory, value co-creation, and consumer decision-making - are required to account for CAIA-specific acceptance dynamics?

By addressing these questions, this SLR provides a comprehensive understanding of consumer engagement, evaluation, and acceptance of CAIA, guiding both academic research and practical implementation in marketing and service contexts.

## 2. Theoretical Background

### *2.1 Artificial Intelligence and Conversational AI Agents*

McCarthy defines Artificial Intelligence (AI) as the field aimed at creating systems that exhibit human-level intelligence by enabling them to operate in a 'common sense informatic situation' (McCarthy, 2007). Conversational agents (CAs) engage in natural language interactions with users, facilitating access to information and services through dialogue-based text or voice interfaces (Følstad et al., 2019). CAIAs combine natural language interaction and dialogue management with AI technologies like machine learning and natural language processing, enabling real-time, human-like responses (Raut et al., 2024). While traditional CAs excel in structured, rule-based interactions, CAIAs differ by dynamically adapting to diverse scenarios, personalizing responses, and managing context, making them suited for complex, high-value applications across industries (Kelly et al., 2022).

### *2.2 Customer Acceptance of CAIAs: A Marketing Perspective*

Customer acceptance of CAIAs is a complex phenomenon influenced by multiple determinants (Mariani et al., 2023). Behavioral intention is shaped by psychological, social, and environmental determinants (Davis, 1993). Determinants such as the agent's ability to provide accurate and timely responses, resolve complex queries, and emulate human-like communication styles play a pivotal role in shaping acceptance (Adam et al., 2021; Hsu and Lin, 2023).

Viewed through a marketing lens, CAIA acceptance cannot be divorced from consumer decision-making and relationship cultivation. CAIAs participate in value co-creation (Vargo and Lusch, 2004), shaping product perceptions, steering purchase decisions, and mediating post-purchase service encounters - functioning as boundary-spanning actors across the customer journey (Lemon and Verhoef, 2016). Whether a consumer accepts a CAIA depends not only on functional criteria but on the agent's contribution to customer value at the particular journey stage. A CAIA generating tailored product suggestions plays a different role from one managing complaint resolution; the former operates as a co-creator of experiential value, the latter as a relational intermediary. These distinct roles activate different acceptance mechanisms-a differentiation the literature has acknowledged only in passing.

### *2.3 Theoretical Tensions: Why Established Models Struggle with CAIAs*

Several features peculiar to CAIAs place considerable strain on the assumptions underpinning established acceptance models.

The first concerns adaptivity and, relatedly, non-stationarity. Both TAM and UTAUT treat a system's perceived attributes - usefulness, ease of use - as properties that are sufficiently stable for users to evaluate at a discrete point in time. With CAIAs, this assumption is difficult to sustain. Because these agents learn from interactions, their competence, response quality, and even 'tone' may shift noticeably between encounters (Chandra et al., 2022). A user's assessment of perceived usefulness at time $t_1$ may therefore bear little resemblance to the reality at time $t_2$ ; not because the user's perceptions have drifted, but because the object of evaluation has itself changed. Cross-sectional surveys, which remain the dominant methodology in the reviewed literature, essentially attempt to pin down a moving target. The inconsistent effect sizes for perceived usefulness reported across studies in our sample may, in part, reflect precisely this measurement artefact.

Second, traditional acceptance models rest on the implicit assumption of relatively stable and predictable system behaviour, such that similar inputs are expected to generate comparable outputs. CAIAs, rooted in probabilistic inference, violate this expectation: the same query can produce divergent responses depending on context and stochastic processes internal to the model (Ling et al., 2023; Ng, 2024). UTAUT's 'effort expectancy' construct presupposes that users can gauge how much effort an interaction will demand; where system behaviour is inherently uncertain, such estimation becomes precarious. Trust formation is likewise affected. In deterministic systems, trust is grounded in predictability (Mayer et al., 1995). When predictability cannot be guaranteed, trust must draw on other sources: competence inferences, institutional reputation, or affective attachment. Existing models offer little guidance on these alternative pathways.

Third, CAIAs occupy an ambiguous ontological position between tool and social actor. According to the CASA paradigm (Nass et al., 1994), users tend to transfer social expectations and normative interaction patterns to computer-mediated systems, attributing to them qualities typically reserved for human interaction partners. TAM, by contrast, conceptualises technology as an instrument to be weighed on functional grounds alone. These two logics yield contradictory predictions. Under CASA, anthropomorphic cues should boost acceptance via social presence and relational engagement; under TAM, acceptance ought to be governed by instrumental utility, and anthropomorphic flourishes that do not improve task performance are theoretically irrelevant. Empirical work indicates that both mechanisms are at play simultaneously (Adam et al., 2021; Zhang et al., 2024), yet their relative salience appears to depend on context. In high-stakes environments such as banking or financial advisory, instrumental rationality tends to dominate; in more hedonic, low-stakes settings like e-commerce browsing, social response mechanisms gain the upper hand. No existing framework accounts for this context-contingent interplay in a systematic way.

## 3. Methodology

### *3.1 Literature Search Strategy and Identification Process*

This SLR employed a systematic approach to identify and analyze relevant research on acceptance and adoption of CAIA following the PRISMA method (Moher et al., 2009). SLRs provide a rigorous framework for evaluating and synthesizing scholarly literature, especially in management, marketing, and social sciences (Sauer and Seuring, 2023). To ensure conceptual clarity, we developed a structured search term strategy encompassing variations of core concepts relevant to acceptance of CAIA. Table 1 presents the terms, each selected to reflect theoretical and empirical constructs in the literature on technology adoption and user perception (Davis, 1989; Venkatesh et al., 2003).

*(Insert Table 1 here)*

To ensure the retrieval of directly relevant literature, we incorporated the terms 'AI' and 'conversational AI,' supplemented synonyms for 'conversational agent' (e.g., 'chatbot,' 'assistant') to capture terminological diversity (Adam et al., 2021), and deliberately excluded broader descriptors such as 'machine learning' and 'deep learning' to prevent inclusion of tangential studies. We searched Scopus, Web of Science, EBSCO, EconBIZ, and ScienceDirect in April 2025 (see Figure 1).

*(Insert Figure 1 here)*

### *3.2 Screening and Selection Process*

After initial screening, 509 articles were identified. Following deduplication (n = 241), 268 articles remained. A three-stage process was used to identify relevant literature: First, articles unrelated to business subjects (e.g., clinical medicine, pedagogical technology, computational linguistics) were excluded, removing 90 publications and leaving 149. Second, a two-stage filtering process (abstract evaluation and full-text examination) removed 104 articles, leaving 45 for analysis. Lastly, citation analyses (backward and forward) added 13 articles, resulting in a final sample of 58 publications.

To safeguard methodological rigour, a formal decision-verification process was employed. A structured protocol specified inclusion criteria: studies had to (a) report empirical findings on CAIA acceptance, adoption, or continued-use intention, (b) address a customer-facing context, (c) examine a text-based system with demonstrable AI capabilities, and (d) have appeared in a peer-reviewed English-language journal between 2018 and 2025. Articles were excluded if they dealt exclusively with voice-only assistants, internal organisational tools, purely conceptual designs, or rule-based chatbots lacking AI functionality. For instance, work on Siri's voice mode or deterministic FAQ bots was excluded, whereas research on GPT-based service agents met the threshold.

### *3.3 Data Analysis*

The annual number of publications demonstrates a steady increase in research activity. Starting with minimal publications in 2019, the number grows incrementally from 2020 to 2022, followed by a significant surge in 2023, which marks the peak. This trend highlights the topic's growing relevance. To understand how the focus of this expanding literature has evolved, we analyzed the frequency of higher-order determinant categories. The dataset was aggregated by publication year and determinant classification, and the resulting frequencies were visualized as a stacked-area chart (see Figure 2).

*(Insert Figure 2 here)*

The sectoral distribution reveals a predominant focus on e-commerce at 34% (20 articles), followed by financial services at 22% (13 articles). Studies covering multiple sectors make up 17% (10 articles). Research without a specific sector accounts for 14% (8 articles), while travel, tourism, and hospitality contributes 10% (6 articles) and online telecommunications 2% (1 article). Our analysis further reveals that quantitative research dominates the sample at 79.3% (46 articles). Among these, surveys account for 50.0% (29 articles), followed by experiments at 29.3% (17 articles). Qualitative research makes up 6.9% (4 articles), while mixed-methods research constitutes 13.8% (8 articles). The sparse use of qualitative and mixed methods suggests that in-depth, contextualized insights into CAIA acceptance remain underexplored.

## 4. Findings

The determinants of acceptance of CAIA are summarized in Table 2, complemented by Figure 2 illustrating the evolution of each predominant determinant from 2019 to 2025.

*(Insert Table 2 here)*

### *4.1 Perceived Risk and Trust*

Perceived Risk (PR), as defined by Dowling and Staelin (1994), refers to consumers' perceptions of uncertainty and potential negative outcomes related to technology usage. The opacity of high-performing AI models complicates building user trust, as mismatched trust levels can lead to over-reliance or under-utilization. Trust evolves through emotional, cognitive, and organizational dimensions (Mayer et al., 1995). It is non-calculative and triggered by anthropomorphic features in CAIA, fostering acceptance and resilience (Gkinko and Elbanna, 2023b). Zhang et al. (2024) highlight that emotional cues enhance perceived humanness, deepening user connections.

Cognitive trust refers to users' belief in CAIA's competence and reliability, based on rational evaluation. Raut et al. (2024) emphasize that transparency in AI decisions enhances cognitive trust. Ng (2024) highlights repeated use and positive feedback loops as critical for strengthening trust. Organizational trust involves confidence in the institution providing the CAIA (Gkinko and Elbanna, 2023a). Privacy emerges as a core pillar of sustained trust, with transparent data practices mitigating privacy risks (Cheng and Jiang, 2020). Khan and Mishra (2024) demonstrate how AI credibility positively influences consumer–AI experiences.

An important boundary condition surfaces when the analysis differentiates between high-stakes and low-stakes decision environments. In domains where personal consequences are considerable, such as banking (Cintamür, 2024) and financial advisory (Zhu et al., 2024), perceived risk operates as a dominant inhibitor of adoption, suppressing acceptance even where the CAIA performs well on functional grounds. The picture differs in low-stakes e-commerce settings, where hedonic motivation and social presence cues attenuate risk perceptions substantially (Sidlauskiene et al., 2023; Yao and Xi, 2024). This pattern reveals a limitation of TAM's treatment of risk as a generic moderator: the model provides no mechanism for the severity of the decision at hand. In high-stakes environments, trust reflects a relational evaluation of the CAIA's perceived competence as a partner, a dimension that is not explicitly theorized within TAM's functional construct architecture.

### *4.2 Perceived Ease of Use and Perceived Usefulness*

Perceived ease of use (PEOU), defined by Davis (1989) as 'the degree to which a person believes that using a particular system would be free of effort,' is shaped by intuitive design, seamless interaction capabilities, and the system's ability to accurately respond to user inputs. Figure 2 shows a consistent increase in publications addressing

PEOU. Perceived usefulness (PU), 'the degree to which a person believes that using a particular system would enhance his or her job performance' (Davis, 1989), is a dominant determinant of CAIA acceptance. When users expect CAIA to improve task efficiency, adoption intentions increase (Raut et al., 2024). PU is strengthened by PEOU (Davis, 1989), and PU mediates the link between need certainty and acceptance (Ng, 2024).

There are, however, grounds for questioning whether PU and PEOU can be treated as stable constructs in the CAIA context. Because a CAIA's outputs evolve through continued use, perceived usefulness is less a fixed system property than an emergent property of the user–system relationship. For TAM-based studies relying on single-timepoint surveys, this dynamism poses a non-trivial measurement problem. The PU–PEOU interaction also varies by agent type. Utilitarian agents (task-efficiency bots, FAQ assistants) tend to be evaluated through the PU lens, consistent with TAM. Relational agents seem to be evaluated along dimensions PU only partially captures: social presence, perceived empathy, and a sense of being 'understood' (Wang et al., 2025; Priya and Sharma, 2023). The parallel with the marketing distinction between utilitarian and hedonic consumption motives (Zeithaml, 1988) warrants more systematic investigation.



### *4.3 Social Presence and Anthropomorphism*

Social presence, defined as the degree to which users perceive CAIA as socially aware entities, is pivotal in determining acceptance. Empirical findings consistently highlight that anthropomorphic features such as human-like language and verbal design cues, enhance perceived social presence, fostering trust and emotional engagement (Adam et al., 2021). In conversational commerce, anthropomorphic verbal cues increase perceptions of product personalization, heightening willingness to pay (Hsu and Lin, 2023; Mulcahy et al., 2024). These effects were pronounced among users experiencing situational loneliness (Sidlauskiene et al., 2023).

Several studies show that social presence is context-sensitive, moderated by individual characteristics and task complexity. In service recovery contexts, communal-oriented users respond more positively to social-oriented chatbots, while exchange-oriented users favor task-oriented designs (Wang et al., 2025). In high-complexity tasks, users tend to favor social-oriented chatbots for empathetic and personalized responses. Users' situational emotions further modulate the effect: lonely users anthropomorphize chatbots more strongly (Aumüller et al., 2024; Wang et al., 2025).

Taken together, these findings bring into relief a tension between TAM's instrumentalism and CASA's social response logic. Our reading of the evidence suggests that these mechanisms are context-contingent, and the customer journey offers a useful organising framework. During the pre-purchase phase, social presence cues lower psychological distance and foster engagement. In the purchase phase, where accuracy and transactional fluency are paramount, instrumental utility reasserts its primacy. The post-purchase phase, particularly service recovery, seems to require both: functional competence (problem resolution) alongside relational competence (empathy, acknowledgement). Such a journey-contingent account represents a meaningful departure from the one-size-fits-all logic that has characterised much of the acceptance literature.

### *4.4 Service Quality*

Service quality, defined as the degree to which a service is perceived as superior (Zeithaml, 1988), has regained prominence in CAIA research. Perceived intelligence, capturing the agent's ability to understand and respond appropriately to user input, represents a central component of this construct (Gieselmann and Sassenberg, 2023). Personalization, information quality (accuracy, relevance, completeness), and perceived customization emerge as additional dimensions (Chen et al., 2022; Ling et al., 2023; Priya and Sharma, 2023).

A value co-creation perspective (Vargo and Lusch, 2004) casts this differently. Service quality in a CAIA interaction is not simply a provider-side attribute; it is a co-produced outcome. The usefulness of the information a CAIA delivers depends on its algorithms, the user's capacity to articulate needs, and the iterative process through which mutual understanding is refined. This co-productive dynamic sets CAIA service quality apart from traditional metrics: it is emergent, dialogical, and contingent on the user–agent relationship. In high-stakes domains, information quality appears a hygiene factor; its absence undermines acceptance, but its presence alone does little without trust. In low-stakes settings, it operates as a delight factor, amplifying hedonic gratification (Ng, 2024).

### *4.5 User Characteristics*

Customer acceptance is shaped by technology readiness, prior AI experience, technology anxiety, hedonic motivation, and demographic traits. Technology readiness (Parasuraman, 2000) positively influences perceived usefulness and ease of use (Raut et al., 2024). In contrast, technology anxiety serves as a barrier, reducing emotional trust even when CAIA performs adequately (Cintamür, 2024). Prior experience reduces perceived risk and enhances trust (Gieselmann and Sassenberg, 2023). Hedonic motivation increases continued usage intention (Ng, 2024; Venkatesh et al., 2012).

Demographic patterns remain equivocal. Age is the most consistent predictor: older users tend toward greater scepticism (Zhu et al., 2022). Some gender differences exist, but effects for income, education, and cultural background are inconclusive (Yao and Xi, 2024). More telling is how user characteristics interact with agent type and decision context. Technology anxiety exerts a markedly stronger dampening effect in high-stakes contexts like banking than in low-stakes settings. Conversely, hedonic motivation appears a better predictor of acceptance for relational agents than for utilitarian ones, presumably because relational agents offer forms of social and emotional gratification that utilitarian agents, by design, do not.

### *4.6 Environmental Determinants*

CAIA acceptance is influenced by social influence, cultural norms, and regulatory environments. Based on Venkatesh et al. (2003), social influence shapes behavioral intention when individuals in a user's social environment share positive experiences with CAIAs (Gursoy et al., 2019; Cintamür, 2024). High-context cultures, which value implicit communication and relational cues, prefer AI systems emphasizing social presence (Chen et al., 2022; Hsu and Lin, 2023). Conversely, low-context cultures prioritizing task efficiency favor performance-oriented utility (Haoyue and Cho, 2024; Yao and Xi, 2024).

## 5. Predominant Theoretical Lenses

Within the final sample, 47 distinct theoretical frameworks were identified. The five most frequently applied theories are presented in Table 3.

*(Insert Table 3 here)*

### *5.1 Overview of Applied Theories*

TAM (Davis, 1989) was the most frequently used framework in our SLR. Despite its predictive power, the model overlooks social, organizational, and contextual determinants. Recent studies expanded TAM by incorporating anthropomorphism (Liu et al., 2024), perceived intelligence (Pillai and Sivathanu, 2020), trust (Kelly et al., 2022), and social presence (Priya and Sharma, 2023). BRT expands on traditional models by focusing on how individuals weigh specific reasons for and against adoption (Westaby, 2005). Jan et al. (2023) apply BRT to CAIA shopping contexts. Uses and Gratifications Theory (U&G) posits that individuals select media based on expected gratifications (Katz et al., 1973). Ng (2024) shows that intrinsic motivations drive continued acceptance. The CASA paradigm demonstrates that humans treat computers as social beings (Nass et al., 1994). Adam et al. (2021) demonstrate that users apply social norms to CAIA. UTAUT (Venkatesh et al., 2003, 2012) identifies performance expectancy, effort expectancy, and social influence as key predictors. Miraz et al. (2024) apply UTAUT to CAIA in CRM contexts.

### *5.2 Toward a Theoretical Dialogue: Reconciling Competing Logics*

The frameworks dominating CAIA acceptance research rest on distinct assumptions about how humans relate to technology, generating divergent predictions. A productive synthesis must make these logics explicit and specify the conditions under which each holds.

TAM and UTAUT share an instrumentally rational foundation. The user evaluates a technology on the basis of anticipated functional outcomes - usefulness, effort, performance - and the relationship is essentially transactional. The logic is persuasive for utilitarian agents in unambiguous task contexts: when a consumer interacts with an order-tracking chatbot, the evaluation is predominantly instrumental, and TAM's constructs capture what matters.

CASA rests on a different premise. Users project social norms and emotional responses onto technological artefacts; the user–system relationship is relational rather than transactional. This logic explains phenomena TAM cannot accommodate why users feel 'let down' when a CAIA fails to show empathy during service recovery (Wang et al., 2025), or why anthropomorphic cues improve compliance despite adding nothing to functional performance (Adam et al., 2021). CASA proves most illuminating for relational agents and emotionally charged contexts.

BRT sits between these poles, modelling the deliberate weighing of reasons for and against adoption. It accommodates both instrumental and social considerations but does not capture CASA's automatic social responses. U&G broadens the picture by privileging intrinsic gratifications such as enjoyment and curiosity that are underspecified in both TAM and CASA.

On the basis of our synthesis, we propose a context-contingent integration. In utilitarian, low-stakes settings, TAM's instrumental logic functions as the primary mechanism, with CASA effects playing a supporting role. In relational contexts, the hierarchy reverses: CASA's social response logic becomes primary, while TAM constructs serve as necessary but insufficient preconditions. High-stakes contexts seem better served by BRT's dual-factor architecture; U&G helps account for sustained engagement across settings. This perspective moves the field toward a contingency model mapping theoretical mechanisms to interaction-context characteristics.

## 6. Discussion and Synthesis

To the best of our knowledge, this review constitutes the first systematic attempt not merely to catalogue the determinants of CAIA acceptance but to interrogate the theoretical adequacy of the frameworks through which those determinants have been studied. In response to RQ1, the analysis delineates seven principal categories of acceptance determinants, encompassing 26 subordinate variables (see Table 2). Yet the more substantive contribution lies in demonstrating that the magnitude and, at times, the direction of these determinants is systematically conditioned by two moderating dimensions that have received insufficient attention: the type of agent (utilitarian versus relational) and the decisional context (high-stakes versus low-stakes).

Addressing RQ2, our synthesis points to an uncomfortable conclusion: TAM and UTAUT retain explanatory power for utilitarian agents in instrumentally oriented settings, but prove inadequate on three fronts. They cannot account for (a) the non-stationarity of perceived attributes in systems that learn, (b) the social pathways through which anthropomorphic cues affect acceptance independently of utility, or (c) the co-creative dynamics where service quality emerges from the user–agent dyad rather than residing in the system alone. CASA compensates for (b) but lacks vocabulary for functional evaluation; no single framework addresses all three. This fragmentation, we contend, accounts for the contradictory findings that recur when different lenses are applied to similar phenomena.

Anchoring CAIA acceptance research in marketing-specific constructs such as the customer journey, value co-creation, and relationship management provides a disciplinary home that this body of work has largely lacked. Mapping acceptance mechanisms onto journey phases explains findings that appear contradictory in the aggregate: social presence enhances acceptance during pre-purchase exploration but contributes little during the purchase transaction, where speed and accuracy take precedence. Adopting a co-creation lens repositions service quality from a static provider attribute to a jointly produced outcome, an interpretation that is more consonant with contemporary marketing scholarship (Vargo and Lusch, 2004) than with the input–output logic inherited from the IS tradition.

**These contributions can be situated within recent marketing-oriented reviews of conversational agents. Mariani et al. (2023) map the field through bibliographic coupling, identifying four thematic clusters (trust, NLP design,**

**communication, and value creation) and a broad driver framework that encompasses text- and voice-based agents alike. The present review shares their interest in synthesising acceptance determinants but narrows the scope to text-based CAIAs and adds a diagnostic layer that examines why the acceptance models applied to them produce contradictory findings. Ramesh and Chawla (2022) pursue a complementary aim through morphological and co-occurrence analyses that decompose the chatbot domain into 11 dimensions and 264 variants, exposing under-explored configurations. Where their decomposition reveals what has not yet been studied, the present work asks whether the theoretical assumptions of the models that have been applied are suited to the phenomena under investigation. The two approaches thus complement one another: morphological mapping locates blank spaces on the research landscape, theoretical critique explains why certain populated spaces have produced inconsistent results. Gelbrich et al. (2026) offer the most comprehensive meta-analytic treatment of automated agents in marketing to date, synthesising 943 effect sizes from 327 studies. Their finding that each agent type (robot, chatbot, algorithm) carries its own set of contingencies resonates with our distinction between utilitarian and relational agents, though the two studies arrive at this differentiation from different angles. Fares et al. (2026) complement these efforts with a meta-analysis focused specifically on consumer acceptance, consolidating which determinant links are robust. The present review extends that line of inquiry by tracing the observed effect heterogeneity to its theoretical source: the mismatch between static acceptance frameworks and non-stationary AI systems. Collectively, these reviews form a coherent body of work. The present study contributes a theoretically grounded diagnosis of framework inadequacy, anchored in marketing-specific**

**constructs, that positions CAIA acceptance as a marketing phenomenon rather than a purely technology-centred one.**

## 7. Implications

### *7.1 Theoretical Implications*

The theoretical landscape surrounding CAIA acceptance is changing. As Figure 2 illustrates, risk-related constructs have gained prominence since 2022, eclipsing PU as the most frequently examined determinant by 2023 - a shift mirroring the broader preoccupation with trust, privacy, and transparency in human–AI encounters. The concurrent rise of interest in affective capabilities underscores that the emotional register of human–agent interaction can no longer be treated as peripheral. But the central implication goes beyond model incompleteness. The deeper problem is structural misalignment: TAM and UTAUT were designed for technologies whose attributes remain fixed and whose evaluation is instrumental; CAIAs are adaptive systems whose evaluation straddles the instrumental and the relational. The field therefore needs to move beyond accretion toward reconceptualisation: models handling non-stationarity, probabilistic behaviour, and dual-process evaluation. The context-contingent integration in Section 5.2 offers one starting point.



### *7.2 Managerial Implications*

During the pre-purchase phase, our evidence suggests relational agent characteristics are most consequential. Social presence cues such as natural conversational style, an empathetic register, and recall of prior interactions foster rapport that encourages exploration. Managers should prioritise conversational personalisation and recommendation quality, positioning the CAIA as a knowledgeable advisor.

The purchase phase, by contrast, calls for a more utilitarian orientation. Speed, accuracy, and frictionless integration with payment and fulfilment systems become paramount, and acceptance is driven overwhelmingly by perceived usefulness and ease of use. At this stage, anthropomorphic embellishments that slow the transaction or introduce unnecessary conversational turns are more likely to irritate than to engage.

Post-purchase interactions, particularly service recovery, represent the most challenging design context, requiring both relational and functional competence. Users need empathetic acknowledgement alongside efficient problem resolution. CAIAs that modulate their communication style by shifting between social-oriented and task-oriented modes depending on the emotional tenor of the exchange are better positioned to satisfy these dual expectations (Wang et al., 2025).

In high-stakes domains such as banking, financial advisory, or healthcare, trust-building warrants a proactive, institutional approach. Algorithmic transparency features, data-security certifications, and clearly communicated escalation protocols to human agents are likely indispensable. Given that technology anxiety is a stronger barrier here, interface simplification and unambiguous opt-out pathways deserve particular attention (Cintamür, 2024; Zhu et al., 2024).

In low-stakes environments such as e-commerce browsing, lifestyle content, entertainment, hedonic motivation and social presence tend to be the primary drivers of engagement. Here, managers can afford to experiment more freely with anthropomorphic features, playful interaction designs, and deeper personalisation, without triggering the privacy backlash that such features are apt to provoke in contexts where the stakes are higher.

### *7.3 Future Research Directions*

A first and pressing concern is the temporal dimension of CAIA acceptance. Because

CAIAs are non-stationary, it remains unclear how consumers form stable acceptance judgements about a technology in continuous flux. With the exception of Ng (2024), studies in our sample are overwhelmingly cross-sectional. Longitudinal designs tracking perceived usefulness and trust across multiple encounters would illuminate whether acceptance trajectories converge or remain volatile. Experience-sampling methods and panel designs would also help disentangle system improvement from user habituation.

A second area concerns the boundary conditions governing anthropomorphism. Anthropomorphic cues can enhance acceptance through social presence but also provoke discomfort or heightened privacy anxiety (Mulcahy et al., 2024). Where the tipping point lies is far from settled. Experimental work parametrically varying the degree and type of anthropomorphism across high-stakes and low-stakes contexts would help delineate the beneficial design envelope. Cultural moderation deserves attention as well, since the threshold at which human-likeness becomes unsettling may differ across societies (Haoyue and Cho, 2024).

Third, the interplay between algorithmic opacity and perceived fairness warrants investigation, especially in service recovery. When a CAIA delivers a compensation decision whose reasoning is opaque, attributional questions arise: does the user hold the agent, the firm, or the algorithm responsible? How do attributions cascade into satisfaction or complaint escalation? Such research would connect the CAIA acceptance agenda to the growing literature on algorithmic justice and carry implications for regulatory compliance.

Fourth, the co-creation dynamics of CAIA encounters deserve closer examination. Interaction quality depends not only on what the system can do but on the user's conversational competence - the ability to specify needs, provide context, and iterate toward a satisfactory outcome. CAIA-mediated service may introduce a digital divide in which articulate users systematically obtain better outcomes. The extent of such a competence gap, and whether proactive dialogue strategies (guided prompts, clarification routines) can narrow it, are questions that have barely been posed.

A fifth direction, rooted in the relationship marketing tradition (Morgan and Hunt, 1994), concerns the evolution of customer–firm relationships through repeated CAIA encounters. As organisations deploy CAIAs for ongoing relationship management, it becomes pertinent to ask whether sustained interaction can shift the customer–firm bond from transactional to relational. Longitudinal field studies in CRM-intensive industries (e.g. banking, insurance, subscription services) would be well placed to explore these questions. Collectively, the directions outlined here offer a research agenda rooted in the tensions this review has identified.

## 8. Limitations

This study is subject to several limitations. First, the review included only English-language publications, which may have excluded relevant findings published in other languages. Second, the scope was limited to text-based CAIA within customer-facing business contexts; the findings may not generalize to voice-based systems or non-commercial applications. Third, the literature search was confined to five major databases. Expanding coverage and incorporating non-English sources may yield broader insights. Fourth, although a formal decision-verification process was employed, the classification of studies by CAIA type (utilitarian vs. relational) and context (high-stakes vs. low-stakes) was performed post hoc, as these distinctions were not consistently reported in the primary studies. Future reviews should develop and validate standardized classification criteria for these dimensions.

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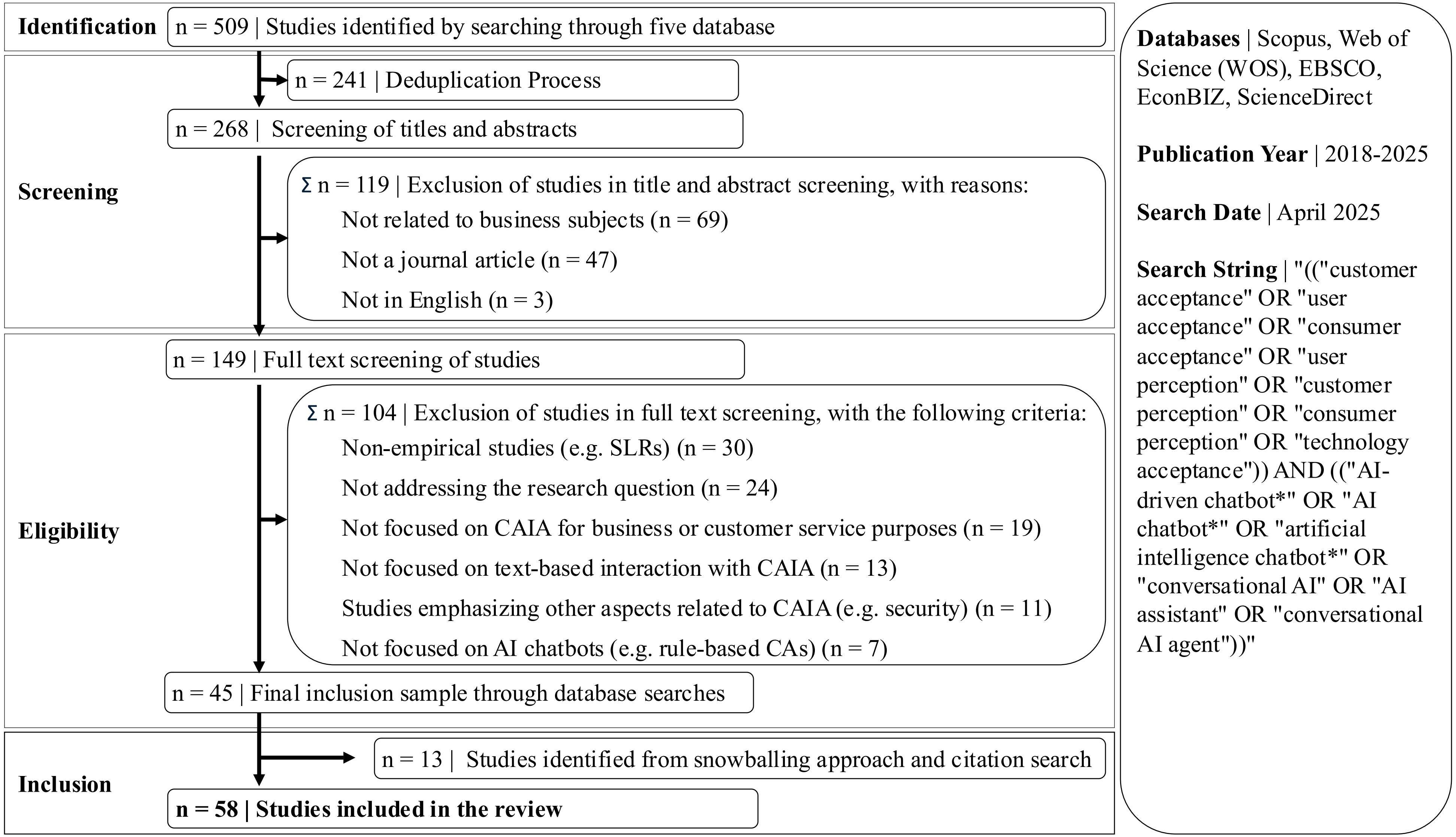


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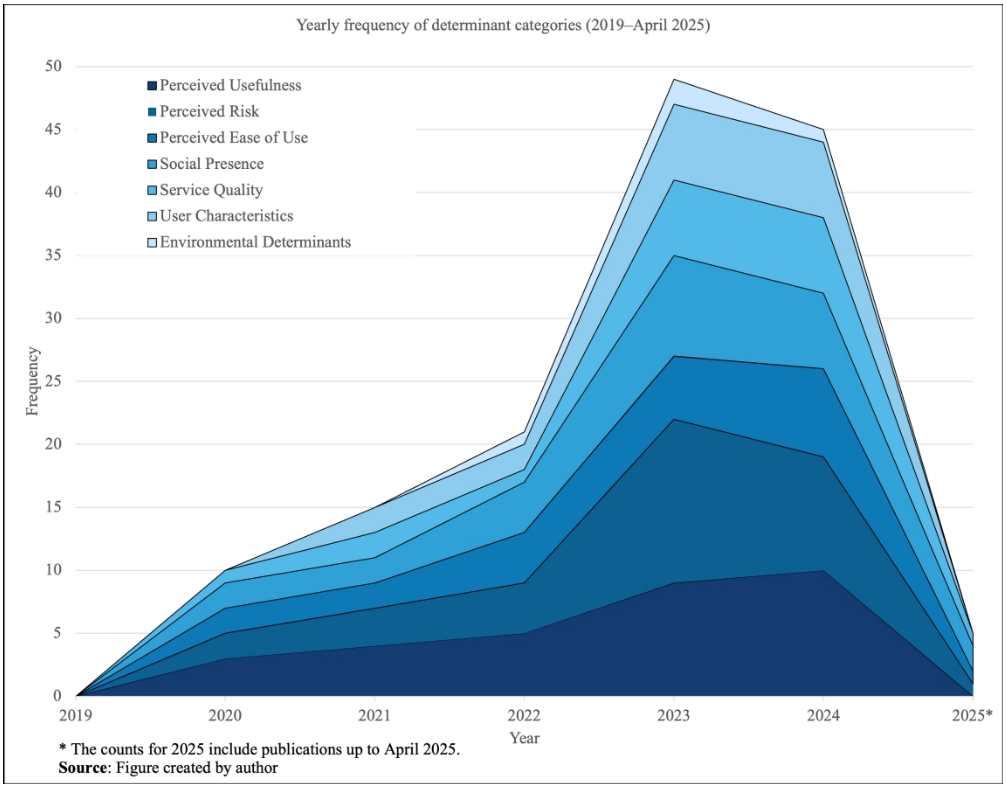


Yearly frequency of determinant categories

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Table 1: Structured Search Term Strategy for the Systematic Literature Review.

| Main Term | Variations | Purpose in the Search Strategy |
|---|---|---|
| Technology acceptance | N/A | Capture studies on the acceptance of technological innovations, essential for understanding user behavior in advanced technology contexts. |
| Customer Acceptance | Consumer Acceptance; User Acceptance | Research addressing acceptance by customers, consumers, or users, terms often used interchangeably in marketing and technology adoption studies and include studies where “user” refers to individuals interacting with technology. |
| Perception | User Perception; Customer Perception; Consumer Perception | Include studies exploring perceptions, attitudes, or beliefs about technology adoption, which are fundamental to modeling acceptance behavior. |
| Artificial Intelligence | Conversational AI; Conversational Agent; AI Chatbot; Chatbot; AI Assistant | Focus the analysis on AI systems capable of engaging in natural interactions with humans, aligned with the specific objectives of the review. |
| Excluded terms | Machine Learning, Deep Learning | Avoidance of broadening the focus to tangential or irrelevant studies related to general AI rather than specifically addressing conversational AI acceptance. |

**Source**: **Self-developed (2026)**

Table 2: Predominant and Subordinates Determinants in CAIA Customer Acceptance Research.

| **Predominant Determinant** | **Subordinate Determinant** | **Description** | **Exemplary Articles** |
|---|---|---|---|
| Perceived Risk | Emotional Trust | Users' trust in the AI's ability to recognize and address their emotional needs. | Gkinko and Elbanna (2023a; b); Meng and Liu (2025); Schreibelmayr, Moradbakhti, and Mara (2023); Sohail *et al.* (2024); Khan and Mishra (2024) |
| | Cognitive Trust | Users' belief in the AI's competence, reliability, and ability to make logical and accurate decisions in interactions. | |
| | Organization Trust | Users' confidence in the institution deploying the AI to act ethically, transparently, and responsibly in managing the technology. | |
| | (Data) Privacy | Protection and ethical handling of users' personal and sensitive data during and after their engagement with AI systems. | |
| | Loss of control | Perceived loss of autonomy and decision-making independence when relying on CAIA. | |
| Perceived Usefulness | Task Efficiency | AI's capability to complete tasks quickly and accurately with minimal user intervention. | Kelly, Kaye, and Oviedo-Trespalacios (2023); Rizomyliotis *et al.* (2022) |
| | Problem-solving Capability | AI's ability to understand complex queries and provide comprehensive solutions. | |
| | Time Savings | Reduction of user effort and time compared to traditional information retrieval methods. | |
| | Service Availability | Consistent, permanent accessibility across multiple platforms and channels. | |
| Perceived Ease of Use | Intuitiveness | User-friendly design that facilitates smooth and natural interaction with the AI system. | Li, Fang, and Chiang (2023); Ng (2024); Suresh *et al.* (2023) |
| | Task Complexity | Complexity of task completion, shaped by cognitive effort or technical knowledge required. | |
| | Accessibility | Adaptability to diverse user abilities, including language support and device compatibility. | |
| | Language Under-standing | Advanced natural language processing enabling context comprehension and nuanced communication. | |
| Social Presence | Anthropomorphism | Degree of AI's human-like communication and interaction traits. | Adam, Wessel, and Benlian (2021); Raut, Goel, and Taneja (2024); Zhu, Liang and |
| | Emotional Connection | Users' psychological ability to form meaningful engagement with the AI system. | |
| | Social Cues | AI's ability to detect and respond to social and emotional cues. | |
| | Personality Traits | Different AI personality configurations influence user perception and acceptance. | |

| | | | |
|---|---|---|---|
| | | | Zhao (2025); Mulcahy *et al.* (2024) |
| Service Quality | Perceived Intelligence | User's assessment of CAIA's capability to comprehend, reply, and engage intelligently. | Bhatnagr and Rajesh (2024); Chen, Le, and Florence (2021) |
| | Information Quality | Precision, relevance, timeliness, and thoroughness of CAIA's information. | |
| | Perceived Custom-ization | Tailored responses and interactions to user preferences, history, and needs. | |
| User Character-istics | Technology Readiness | Individual's psychological predisposition and comfort level with adopting and using new technological innovations. | Cintamür (2024); Fu, Mouakket, and Sun (2023); Zhu *et al.* (2022) |
| | Technology Anxiety | User apprehension and psychological discomfort associated with AI interaction. | |
| | Prior AI Experience | Past experiences with digital technologies and AI shaping user expectations and acceptance. | |
| | Hedonic Motivation | The positive emotional experience and pleasure derived from engaging with CAIA. | |
| | Demographic Determinants | Demographic factors affecting technological adoption, interaction styles and AI views. | |
| Environmental Determinants | Social Influence | Influence of peer advice, social networks, and shared views on AI adoption. | Cintamür (2024); Haoyue and Cho (2024) |
| | Cultural Norms | Societal attitudes, expectations, and acceptance levels regarding AI. | |

**Source: Self-developed (2026)**

Table 3: Predominant Theoretical Lenses in CAIA Customer Acceptance Research.

| | **Theoretical Lens** | **Articles in final sample** | **Exemplary articles** |
|---|---|---|---|
| 1 | Technology Acceptance Model (TAM) | 18 | Liu *et al.* 2024; Ng 2024 |
| 2 | Behavioral Reasoning Theory (BRT) | 4 | Jan, Ji, and Kim 2023; Myin and Watchravesringkan 2024 |
| 3 | Uses and Gratifications Theory (U&G) | 4 | Cheng and Jiang 2020; Kang and Choi 2023 |
| 4 | Computers as Social Actors Paradigm (CASA) | 4 | Aumüller *et al.* 2024; J. Zhang *et al.* 2024 |
| 5 | Unified Theory of Acceptance and Use of Technology (UTAUT) | 3 | Islam and Zhou 2023; Miraz *et al.* 2024 |

**Source: Self-developed (2026)**