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AI-Mediated Communication Beyond Human-AI Dyads: A Systematic Review of Chatbot and Agent Interactions

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ABSTRACT

This study examines recent developments in computer-mediated communication by analysing the role of artificial intelligence within communicative processes. Using a systematic literature review, it explores how AI-based chatbots and AI agents interact with humans and how computer-mediated communication, once viewed as a neutral medium, is shifting toward a more active role. This shift is particularly evident as AI systems increasingly engage directly with users and communicate with other AI systems that mediate human interaction. Drawing on Actor–Network Theory (ANT), the study conceptualises AI technologies as communicative actors that extend beyond their earlier instrumental functions. The review follows the PRISMA framework and analyses studies published between 2015 and 2025. Searches conducted via Mendeley Search initially identified 98 relevant studies, of which 21 met the inclusion criteria focusing on chatbots and AI agents. Findings across multiple domains indicate that AI technologies function within two dominant communication models: the human–AI–human model and the human–AI–AI–human model. The latter demonstrates emerging forms of AI-to-AI communication that mediate human interaction. The study acknowledges limitations related to the rapid evolution of AI, reliance on a single search platform, and potential researcher bias.

Keywords: AI-mediated communication, chatbots, AI agents, Actor-Network Theory, systematic literature review

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1.0 Introduction

In recent years, rapid advances in Artificial Intelligence (AI) have reshaped digital communication and positioned AI at the centre of human–technology interaction. The use of AI systems in communication has expanded at a remarkable pace, and current forecasts indicate that the conversational AI sector may exceed USD 29.8 billion by 2028 (MarketsandMarkets, 2025). In areas such as e-commerce, customer service, education, healthcare, and social media, AI tools including chatbots are now widely employed to support interaction (Adamopoulou & Moussiades, 2020; Baabdullah et al., 2022). Through natural language processing, machine learning, adaptive algorithms, and multimodal interfaces, these systems offer personalised and scalable exchanges that are reshaping both the experience and the expectations of digital communication (Rapp et al., 2021).

The rise of AI-Mediated Communication (AI-MC) points to a wider shift in how technology participates in communication. AI is no longer seen merely as a passive channel for information; it increasingly acts as a mediator that can initiate interaction between humans and digital systems (Hancock et al., 2020). Earlier work in Computer-Mediated Communication (CMC) tended to frame communication as a Human–Computer–Human sequence, in which the computer functioned as a neutral medium rather than a contributor to the exchange (Walther, 1996). As AI technologies have become more embedded in everyday use, this view has moved towards AI-MC, where chatbots and related systems take a more active role in guiding and co-producing interaction.

Current chatbots extend well beyond delivering pre-set responses. They can learn user preferences, sustain multi-turn conversations, and simulate forms of social engagement that appear empathetic (Chaves & Gerosa, 2021; Gnewuch et al., 2017). More advanced systems are often described as intelligent or autonomous agents because they are designed to handle complex tasks and respond to human requirements across different settings. Research has shown examples in driving assistance (Goldman et al., 2020) and in supporting group decision-making through preference elicitation (Nefla et al., 2022). This development aligns with a Human–AI–Human dyadic model, in which humans interact with AI systems that mediate or return interactions to other humans.

Many studies, for example, examine how chatbots enhance efficiency in customer service (Adamopoulou & Moussiades, 2020), support healthcare delivery (El Massari et al., 2025; Wah, 2025), or provide adaptive learning in educational settings (Gligorea et al., 2023; Er-Rafyg et al., 2024). These studies provide valuable insights into performance, user satisfaction, and system usability. Even so, this line of research seldom considers the wider question of how AI systems function as active participants that influence the structure of digital communication networks.

AI systems increasingly adopt relational roles that reach beyond technical execution. They influence user behaviour, shape organisational routines, and affect the wider architecture of digital communication (Hancock et al., 2020). In practice, customer service chatbots not only provide answers to user queries. They also generate data that managers can draw upon when making decisions (Adamopoulou & Moussiades, 2020). In healthcare, dialogue systems supply information while linking to protocols that guide treatment processes (El Massari et al., 2025; Wah, 2025). Through these roles, chatbots and agents interact with humans, other technologies, and institutional rules. This situation prompts several important questions: How do these systems contribute to the formation of digital communication networks? How do they co-exist with human users and organisational structures? And what ethical or societal risks accompany their increasing autonomy?

Existing studies still lack a shared framework for classifying AI chatbots and agents by sophistication, role, mode of interaction, or sector. Some attempts exist, such as distinguishing between task-oriented and social bots (Singh & Beniwal, 2022) categorising interaction by duration and locus of control (Følstad et al., 2019), or developing sector-specific models such as “discover” and “chat” for health care (Martinengo et al., 2023). These approaches remain partial and operate within their own domains, and they do not form a universal model (Vishal & Prabhu, 2023). What is still missing is an integrated classification that spans sectors and levels of sophistication. Much of the current research also remains at the technical layer, leaving aside the question of how AI systems function as relational participants in communication. From this perspective, AI is not only a tool. It is also part of the interaction itself, shaping how messages are produced and managed.

To address this gap, we draw on Actor-Network Theory (ANT) (Latour, 2005; Michael, 2017). ANT proposes that agency is distributed across humans and non-human entities within a network (Belliger & Krieger, 2014; Ochsner & Spöhrer, 2016). In this study, AI systems are treated as actors whose roles emerge through their relations with others. Earlier research often described this mediation in a dyadic arrangement in which a human interacts with an AI and the AI returns a response (Gnewuch et al., 2017; Hancock et al., 2020). Our analysis widens this view to include situations where AI systems also engage with one another before the output is delivered to the user. We refer to this configuration as Human–AI–AI–Human, an emerging pattern of AI-mediated communication that extends beyond the dyad.

This study combines a Systematic Literature Review (SLR) with Actor-Network Theory (ANT) and follows the PRISMA framework to guide the review process (Moher et al., 2009; Page et al., 2021). A total of 98 peer-reviewed studies published between 2015-2025 were synthesised. The study has two aims. The first is to develop a classification framework for AI-mediated communication that identifies the roles of chatbots and agents across different sectors. The second is to examine how these AI entities operate within networks, shaping their formation, maintaining their stability, and contributing to their potential transformation.

The contributions of this study are both theoretical and practical. Theoretically, it improves understanding of AI-mediated communication by applying an actor-network perspective that views AI as part of dynamic communication systems rather than as a separate tool. Practically, it proposes a framework to guide organisations, policymakers, and developers. The framework can support them in planning and managing AI-mediated platforms with attention to responsibility and ethics, especially as communication environments become more complex.

2.0 Literature Review

2.1 Computer-Mediated Communication (CMC)

Early studies of Computer-Mediated Communication (CMC) looked at how digital technologies changed the way people interact. Sproull and Kiesler (1986) argued that electronic mail reduced important social cues such as tone, gestures, and context. From this perspective, computers functioned solely as channels for transmitting messages, and communication through them often appeared less personal, more task-oriented, and more open to misunderstanding.

Walther (1996) later showed that CMC could also create strong social effects. His *hyperpersonal model* explained that when fewer cues were available, people often managed their self-presentation more carefully and formed idealised impressions of others. Under some conditions, this process produced relationships that were even stronger than face-to-face interaction. These studies situated CMC within the Human–Computer–Human model, in which computers influenced the exchange of messages rather than operating as independent actors.

Recent research confirms that CMC continues to be applied in many fields. Bui and Kumar (2023) describe two main forms which are synchronous communication, such as live chat, and asynchronous communication, such as email. They highlight its significance for learning, business, and social media. Even in these updated contexts, computers are still viewed mainly as channels rather than as participants. This limitation indicates a broader movement toward Artificial Intelligence-Mediated Communication (AI-MC), where chatbots and intelligent agents play a more active role by mediating and co-producing communication flows. Recent studies also show that digital platforms shape awareness and influence behavioural change (Briandana et al., 2024), suggesting that AI systems are increasingly positioned as both channels and agents in communication networks.

2.2 AI-Mediated Communication: Evolving Research Landscape

Artificial Intelligence (AI) has become a central topic in digital communication research. Scholars now use the term AI-Mediated Communication (AI-MC) to describe situations in which AI takes an active role in shaping interaction between humans and digital systems, rather than functioning only as a passive tool (Hancock et al., 2020). Chatbots illustrate this shift clearly. They are now used in customer service, e-commerce, health care, education, and even social interaction (Adamopoulou & Moussiades, 2020; Baabdullah et al., 2022). Beyond chatbots, more advanced agent-based systems are being built to adapt to users and manage complex tasks, such as driving assistance (Goldman et al., 2020) or collective decision-making through preference elicitation (Nefla et al., 2022).

In customer service and marketing, AI chatbots have been adopted widely to streamline interactions, reduce operational costs, and strengthen customer satisfaction. Adamopoulou and Moussiades (2020) showed that chatbots can handle customer enquiries effectively through real-time dialogue, while Averineni et al., (2024) examined the integration of AI into customer relationship management (CRM) systems as part of digital marketing strategies. Recent studies also note that generative AI technologies, including ChatGPT, are now used to produce personalised marketing content and to support decision-making processes (Agnihotri & Saravanakumar, 2025; Gołąb-Andrzejak, 2023)

Healthcare represents another field in which AI-MC has expanded rapidly. Chatbots are now used to deliver health information, monitor patients, and support therapy. Kowatsch et al., (2021) , for instance, reviewed conversational agents for chronic disease management and showed their contributions to long-term patient care. Martinengo et al. (2023) proposed frameworks such as "discover" and "chat" to classify and guide the use of healthcare chatbots, while more recent reviews highlight hybrid systems that combine AI with human input to improve trust, safety, and patient engagement (El Massari et al., 2025; Wah, 2025).

In education, adaptive platforms have been developed to offer more personalised support for students. Gligorea et al. (2023) reviewed how these systems can tailor learning paths and contribute to improved engagement and outcomes. Lippert et al. (2020) examined single-agent and multi-agent tutoring designs, showing how these arrangements shape interaction and enable content delivery to adjust in line with learner participation.

Beyond transactional and educational applications, research has also explored the social and emotional dimensions of AI-Mediated Communication. Kouros and Papa (2024) showed how users of AI companions such as *Replika* often form emotional attachments and use these systems as spaces for self-expression and identity exploration. Merrill et al. (2022) demonstrated that the social presence of AI companions increases perceived usefulness and willingness to recommend them, particularly among individuals who experience loneliness. At a cultural and ethical level, Nordmo et al. (2020) investigated gender differences in perceptions of sex and love robots, while Gersen (2019) discussed wider regulatory and moral debates surrounding intimacy with robots within the discourse on *digisexuality*.

The use of AI is also expanding in public administration and government. Sart and Sezgin (2025) describe how AI is being introduced to improve efficiency, decision-making, and service delivery. At the same time, Vatamanu and Tofan (2025) note that adoption in the public sector presents several challenges, including risks of bias, concerns related to cybersecurity, and the need for workforce adaptation.

Scholars have also pointed out a range of ethical and social concerns related to the use of AI in communication. Ali et al. (2025) and Dasilva et al. (2021) describe how deepfakes can be used for harassment, fraud, or political manipulation, creating legal challenges and posing risks for victims. In healthcare, Wah (2025) and Ahmed and Osman (2024) discuss ongoing problems of trust, safety, and bias when chatbots are introduced into sensitive settings. Ellis et al. (Chabot et al., 2024; Ellis et al., 2025) show that many users remain worried about privacy when sharing personal information with AI systems. Beyond healthcare, Chabot et al. (2024) examine the rise of intimate technologies powered by AI, which raises further debates about sexuality, safety, and the social effects of human–machine relations. Recent work has also expanded these concerns to questions of trust in information. Sahebi and Formosa (2025), for example, analyse how AI-Mediated Communication (AI-MC) on social media creates a dilemma in which users must decide whether to trust content that may be unreliable or to become overly cautious in ways that hinder fair judgement. Their study shows that beyond technical performance, AI-MC reshapes the communicative environment by influencing how people assess credibility and reliability in digital interaction.

Studies on AI-mediated communication have provided useful insights in different domains, including marketing (Adamopoulou & Moussiades, 2020; Gołąb-Andrzejak, 2023) healthcare (Kowatsch et al., 2021; Wah, 2025), and education (Gligorea et al., 2023; Lippert et al., 2020) Yet, much of this work remains confined to sector-specific applications. What is still missing is a broader framework that brings these strands together and considers how chatbots and agents, in their different forms, participate in shaping communication across contexts.

2.3 Actor-Network Theory as Conceptual Framework

To address these gaps, this study applies Actor-Network Theory (ANT) as its conceptual lens. ANT, developed by Latour (2005) together with Callon and Law, questions the traditional divide between humans and non-humans by viewing both as actors, which in ANT are described as *actants*, within networks of relations (Belliger & Krieger, 2014; Gallivan, 2024; Michael, 2017). From this standpoint, AI systems such as chatbots and intelligent agents operate as participants that contribute to the shaping and stabilisation of socio-technical networks rather than functioning solely as technical instruments (Zhang & Hu, 2023).

A key idea in ANT is the concept of translation. In this process, actors negotiate roles, align interests, and adjust their connections within the network (Gallivan, 2024; Latour, 2005). ANT does not assign fixed agency to AI systems, instead, it shows how agency develops through their relations with human users, digital infrastructures, regulatory settings, and organisational cultures (Noesgaard et al., 2025; Samarghandi et al., 2023). For example, when an AI chatbot is introduced in customer service, it does more than automate replies. It reshapes workflows, influences user expectations, affects managerial control, and even alters the organisation's identity (Musolino, 2024; Ochsner & Spöhrer, 2016). In this context, chatbots and agents operate as mediators, transforming inputs into new forms of communication rather than simply transferring information from one point to another (Belliger & Krieger, 2014; Zhang & Hu, 2023).

Several studies have used ANT to explore how AI and digital technologies shape communication networks (Marodin et al., 2023; Mogno & Nuccio, 2023; Rao et al., 2024). In media research, Belliger and Krieger (2014) showed that social media platforms function as hybrid networks in which algorithms, users, and organisational interests jointly produce communication flows. Within organisations, Bencherki (2017) explored the ways in which non-human elements such as software and data systems take part in decision-making processes alongside human actors (Samarghandi et al., 2023). Likewise, Ochsner and Spöhrer (2016) used ANT to study digital platforms as constellations of human and technological participants, highlighting how agency is shared across the network (Musolino, 2024)

By applying ANT to AI-MC, this study shifts attention from narrow functional measures of chatbots toward the wider relational ways AI entities contribute to digital communication networks. ANT reveals how chatbots and agents negotiate roles with users, organisations, and infrastructures through translation processes that shape communication outcomes. This perspective is increasingly relevant as AI systems learn from experience, coordinate with other technologies, and operate with growing autonomy. Through analysis of the 21 core studies, ANT provides the analytical grounding for the two configurations identified in this review: the Human–AI–Human model, where a single actant mediates the exchange, and the Human–AI–AI–Human configuration, where a front-end chatbot delegates tasks to another AI system before responding to the user. This empirically derived pattern extends ANT scholarship by conceptualising AI not as a single mediator but as a distributed set of networked actants whose relational coordination produces communication outcomes, marking a new stage in actor-network communication where agency is shared across multiple AI systems.

3.0 Methods

This study used a Systematic Literature Review (SLR) guided by the PRISMA framework (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to synthesise research on AI-Mediated Communication (AI-MC). The SLR approach offered a transparent and replicable process for identifying, selecting, and analysing relevant studies, helping to maintain methodological rigour and reduce potential bias (Moher et al., 2009; Page et al., 2021). This method is well suited to AI-MC since the field is still developing and draws on knowledge from multiple disciplines and areas of application. The review was carried out in full accordance with the PRISMA 2020 guidelines.

The review began with a central research objective: to map classifications of AI chatbots and agents and to examine their roles within digital communication networks. Rather than concentrating solely on technical features, the study considered how AI entities operate as actors that are embedded within socio-technical systems of communication. The literature search was conducted using Mendeley Search, which functioned as the main database aggregator for identifying relevant publications. This tool offers integrated access to multiple scholarly databases and enabled the retrieval of studies from journals, conference proceedings, and academic repositories. Mendeley Search aggregated records from major scholarly sources, including Scopus, Web of Science, IEEE Xplore, ACM Digital Library, SpringerLink, CrossRef, PubMed/PMC, DOAJ, and publisher-specific databases such as Wiley Online Library, Taylor & Francis Online, IGI Global, and MDPI. Although the specific indexing source, such as Scopus, IEEE, DOAJ, or ACM, was not always recorded, the review maintained scholarly quality by including only peer-reviewed articles. The search employed keyword combinations that included "AI-Mediated Communication," "AI Chatbot in Digital Communication," "AI Agent Classification," and "Artificial Intelligence in Media and Communication." These keywords were entered as natural-language search phrases, in line with Mendeley Search's non-Boolean query format, and were expanded semantically by the platform across its aggregated databases. This strategy supported the inclusion of international and regional studies and produced a dataset with varied disciplinary perspectives. The final search was completed in June 2025, shortly before the initial submission of this manuscript. As the study relied exclusively on secondary analysis of published literature, no review protocol was registered or prepared.

The initial search generated a substantial number of articles from a wide range of disciplines. In the PRISMA identification stage, all retrieved records were gathered through Mendeley Search and included journal articles, conference papers, book chapters, and academic reports. To ensure quality and relevance, a multi-stage screening process was applied. Titles and abstracts were reviewed first to remove duplicates and to exclude studies that fell outside the scope of communication-focused AI research. This stage removed publications that did not address AI-mediated communication or that examined system engineering without any communicative dimension. For the purposes of this review, "non-communicative AI" referred to AI systems that do not generate messages, outputs, or interactional content for users (e.g., predictive algorithms, classifiers, or back-end NLP models), while "technical design–only studies" referred to publications focused solely on system architecture or model performance without any user interaction or communicative processes. Full texts were then evaluated against the inclusion criteria, which required explicit attention to AI chatbots or agents within digital communication contexts. During the eligibility stage, non–peer reviewed materials, unavailable full texts, and publications outside the 2015–2025 range were also excluded.

Only peer-reviewed articles and recognised academic reports published between 2015-2025 were retained to ensure contemporary relevance. Screening and eligibility checks were carried out collaboratively by all four authors, who reviewed records independently before discussing any disagreements to reach a shared conclusion. This independent–review and consensus procedure served as the primary safeguard against screening bias. A PRISMA flow diagram that summarises the identification, screening, eligibility assessment, and final inclusion of studies is available in Appendix B.

After the screening process, 98 publications met the broad inclusion criteria. Consistent with qualitative systematic review practices and the study's Actor–Network Theory (ANT) orientation, the analysis adopted a two-tiered synthesis strategy. While all 98 studies informed the descriptive mapping of the field, only studies that provided explicit discussion of communicative agency, mediation processes, or the relational roles of AI systems were included in the core qualitative analysis.

Based on these predefined analytical criteria, 21 studies were selected for full thematic coding. These studies were fully retrievable, methodologically transparent, and directly addressed how AI chatbots and AI agents function as interactional actors within communication networks. Publications that focused primarily on technical system design, performance optimisation, or non-communicative AI applications without substantive engagement with interactional processes were excluded from the core analytical corpus.

The 21 selected studies therefore constitute the core dataset for in-depth thematic analysis, while the broader set of 98 publications is reflected in the PRISMA flow diagram and informs the narrative synthesis. Thematic analysis focused on identifying recurring patterns, application domains, and modes of interaction associated with AI-mediated communication. Data extraction captured the type of AI system, communicative function, application sector, interaction modality, methodological approach, and reported outcomes. This targeted analytical strategy enabled conceptual depth while maintaining methodological transparency. The full list of core studies is provided in Appendix A.

Because the review synthesised conceptual and qualitative findings rather than effect sizes, no statistical effect measures were applied, and no meta-analysis was conducted. Beyond functional classifications, the analysis also considered ethical and socio-technical issues, including user trust, data privacy, algorithmic bias, and the wider societal impact of AI-mediated interactions (Nadarzynski et al., 2020). This broader perspective made it possible to understand AI as both a technical tool and an evolving participant in complex communication systems. No formal risk-of-bias instrument was used due to the conceptual and heterogeneous nature of the included studies. Even so, attention was given to transparency, clarity of research design, and peer-review status to help reduce interpretive bias.

To move beyond descriptive categorisation, this study used Actor-Network Theory (ANT) as its analytical lens. ANT, as developed by Latour (2005), sees both humans and AI systems as participants in networks shaped by ongoing negotiation and shifting relations. Recent studies show how conversational agents pose significant challenges in natural language understanding, especially in low-resource contexts (Uzoaru et al., 2025), and how chatbots are being designed to support digital governance and organisational services (Bouras et al., 2024). Guided by this perspective, the analysis examined how chatbots and agents engage in translation processes by negotiating roles, adjusting communication practices, and helping to construct interaction structures with users, institutions, and technological environments. In the thematic coding process, concepts from ANT, such as actors, actants, translation, and relational agency, guided how interaction patterns were interpreted across the selected studies, ensuring analytical consistency between the empirical themes and the theoretical framework.

The integration of ANT made it possible to view AI's agency in relational terms, positioning these technologies as dynamic participants that both shape and are shaped by their communication environments. This perspective provided the depth needed to examine AI not only as a set of functional systems. It also views them as hybrid actors whose agency develops through complex socio-technical interactions. In doing so, ANT aligns with the study's aim of understanding AI-Mediated Communication as an emergent networked phenomenon.

4.0 Results

A total of 98 studies met the inclusion criteria and were reviewed thematically. From this set, 21 publications were chosen as the core group for closer analysis and are listed in Appendix A, as they best reflected the patterns discussed in this section. The analysis pointed to six main areas in which chatbots, and AI agents are used: customer service and marketing, healthcare, education, social companionship, public administration, and ethical or socio-technical concerns. These areas emerged from recurring themes across different fields. The review also noted a separate pattern of AI-to-AI coordination that cuts across these areas, showing how several systems now work together before a response reaches the user. This cross-cutting pattern emerged inductively as multiple studies described background computational processes that precede the user-facing output.

4.1 AI Chatbots in Customer Service and Marketing

The review showed that AI chatbots are now widely used in customer service and marketing. Studies highlight their role in managing customer inquiries, automating routine tasks, and offering personalised interactions that help strengthen customer relationships (Al-Barrak & Al-Alawi, 2024; Khneyzer et al., 2024). Empirical evidence also suggests a measurable impact on user satisfaction and brand trust, with more than 80% of respondents reporting increased confidence and continued engagement after interacting with AI-driven customer services (Sofiyah et al., 2024).

In sectoral applications, chatbots have reshaped hospitality by improving guest engagement, supporting personalised marketing, and increasing service efficiency (Mei et al., 2024). Within e-commerce platforms, they play an important role in fostering customer trust and dependability, with responsiveness and perceived expertise emerging as key determinants (Christopher et al., 2024). Together, these findings show that chatbots have moved from supporting tools to central components in marketing and customer service strategies.

Overall, these findings indicate that chatbots have moved beyond auxiliary functions and now operate as integral components of digital service communication. This centrality reinforces their role as mediating actors within broader communication networks.

4.2 AI Chatbots in Healthcare Services

In healthcare, chatbots are used for patient support, health education, symptom checking, and remote consultations (Sun & Zhou, 2023). Research shows that they can reduce waiting times and make medical advice more accessible, although challenges remain in areas such as privacy and integration into clinical routines (Sharma et al., 2022).

Over time, these systems have progressed from simple scripted tools to more capable platforms that address a broader range of patient needs (Khan et al., 2025). Still, issues such as user trust and workflow adoption continue to limit their use (Ramesh et al., 2025). As a whole, this domain reveals a persistent tension between technological potential and institutional legitimacy, particularly within high-stakes settings such as healthcare. Such tensions are consistent with ANT's view that the acceptance of non-human actors depends on negotiated legitimacy within existing networks.

4.3 AI Agents in Educational Systems

Recent studies highlight the emergence of intelligent agents as adaptive companions in education. Han et al. (2025) classified the varied roles of learning companion systems and showed how AI agents simulate human-like interaction to enhance personalised learning and strengthen learner motivation. Complementing this, Er-Rafyg et al. (2024) examined the integration of AI in adaptive learning environments and identified both the opportunities for individualised instruction and the challenges linked to ethical and inclusive implementation.

Han et al. (2025) further show that the companion agent relies on separate multimodal learning-analytics engines to determine tailored feedback, indicating that adaptation depends on coordination between a user-facing communicator and a back-end decision module. While invisible to learners, this reflects an early form of distributed AI-to-AI interaction. This concealed analytic chain illustrates how multiple agents jointly shape the communicative output that is eventually presented to the learner.

4.4 AI Agents as Emotional and Social Companions

Beyond practical functions, AI agents are now designed to act as companions in social and emotional ways. Studies show that a sense of *social presence* is important, as it helps people see AI companions as partners and makes interaction feel more natural (Merrill et al., 2022). Other studies show that conversational agents can help reduce loneliness by offering personalised support to individuals who experience social isolation (Alotaibi & Alshahre, 2024). User satisfaction in AI companionship also depends on more than technical performance, with emotional resonance and relational closeness emerging as significant factors in shaping positive experiences (Silayach et al., 2025). This domain shows that AI agents are starting to take part in forms of social interaction that people previously experienced only with other humans. Their participation in these interactions positions them as relational actors rather than mere tools, aligning with ANT's distributed view of agency.

4.5 AI Agents in Public Administration and Governance

Recent research indicates that the use of artificial intelligence in public administration is shifting from routine automation toward more structural forms of change. Mishra et al. (2024) show how governments use chatbots and data-driven systems to increase efficiency, reduce waiting times, and enhance transparency, while also raising issues of bias and accountability. Chen and Gasco-Hernandez (2024) provide empirical evidence from U.S. agencies, showing that chatbots have begun to reshape interactions between officials and citizens. Taken together, these studies suggest that AI agents are now influencing the organisation of governance workflows. These findings illustrate how administrative tasks increasingly depend on coordinated interactions between human and non-human actors.

4.6 Ethical and Socio-Technical Concerns in AI-Mediated Communication

Studies show that alongside functional gains, AI-mediated communication brings a range of ethical and socio-technical risks. Key concerns include data privacy breaches, algorithmic bias, and manipulative uses such as deepfakes, fraud, and online harassment (Akakpo et al., 2025; Burton et al., 2024). These risks are particularly significant in sensitive fields where trust plays a central role. Scholars therefore argue for regulatory approaches that move beyond isolated system-level controls and instead address broader vulnerabilities and the multi-actor dynamics that shape contemporary AI ecosystems (Nah et al., 2024; Skarzyńska et al., 2025). Such dynamics further highlight that communication outcomes arise from networked interactions among heterogeneous actors.

4.7 Emerging AI-to-AI Interactivity Across Platforms

Zeng and Gupta (2025) describe a dual-agent design in which one agent manages the overall process and another delivers the service. This arrangement demonstrates how complex tasks can be divided and completed across different systems, although it has so far been tested only in controlled environments. Similar distributed coordination is also visible in education, where user-facing agents depend on analytics engines to generate personalised output (Han et al., 2025).

Some recent cases in practice point in the same direction. Perplexity connects with OpenTable so that recommendations and bookings happen in a single step (Schwartz, 2025). Google's AI Mode in Search does something similar by linking directly with restaurant reservation systems (Roth, 2025).

Taken together, these examples suggest a shift from a straightforward Human–AI–Human interaction toward a Human–AI–AI–Human model, where multiple agents coordinate before the response reaches the user. This shift reflects ANT's principle of delegation, whereby action is redistributed across linked actors within a network. This development indicates a broader movement toward multi-actor networks that require system-level oversight rather than attention directed solely at individual agents. This alignment across practical and educational systems reinforces the conceptual shift toward multi-agent, relational communication networks consistent with Actor-Network Theory.

4.8 Toward a Systematic Typology of AI-Mediated Communication

Across the reviewed domains, two main models of interaction emerge. In the first, the Human–AI–Human dyadic model, users interact directly with a single chatbot or agent. Organisations in customer service, healthcare, education, and companionship commonly rely on this arrangement, keeping the exchange between one person and one system. In the second, the Human–AI–AI–Human model, a front-end agent works with other AI systems or databases before returning a response to the user. Public administration and cross-platform services often use this model because tasks such as record management, reservations, or policy support require several agents to collaborate.

These two models show how AI-mediated communication now operates through both direct one-to-one exchanges and distributed multi-actor networks, capturing the relational and interconnected behaviour of AI systems described in Actor-Network Theory. Together, they demonstrate how communicative agency is increasingly co-produced across human and non-human nodes within complex socio-technical systems.

5.0 Discussion

It is important to clarify that the Human–AI–AI–Human configuration identified in this review is not defined by technical modularity or backend automation alone. Rather, this model is characterised by *communicative delegation*, in which multiple AI systems sequentially or collaboratively transform meaning, decision logic, or interactional framing before an output is returned to the user. In this configuration, AI-to-AI interaction extends beyond data retrieval or rule execution and involves interpretive or evaluative processes that materially shape the communicative outcome. This distinguishes the model from conventional system architectures, as the communicative act itself is distributed across multiple non-human actors. From an Actor–Network Theory perspective, these AI systems operate as interconnected actants whose coordinated translations produce the message ultimately delivered to the human participant.

Viewed in this broader context, findings across sectors reveal a clear shift in how artificial intelligence functions within communication processes. AI is no longer limited to supporting interaction as a technical intermediary but increasingly operates as an active mediator within AI-mediated communication (AI-MC). In practical terms, AI-based chatbots now engage directly with users across service domains, processing incoming messages and generating responses in line with organisational rules, institutional protocols, or system-level objectives. This development reflects a broader transformation in which communicative agency is progressively shared between human and non-human actors within digitally mediated environments.

Beyond this, there is also what is now referred to as an AI agent. Rather than simply receiving and responding to information, an AI agent is able to carry out more complex forms of interaction according to what it has been instructed to do. Tasks that previously required step-by-step engagement when using computers for communication can now be handled in a more simultaneous manner by these agents. Patterns of AI use such as these align with findings from several studies that record the role of chatbots in customer service, education, and healthcare (Adamopoulou & Moussiades, 2020; Baabdullah et al., 2022; Rapp et al., 2021). These studies also show how AI is being used across a wide range of sectors.

However, the use of AI is not only spread across sectors. The technology itself enables different AI systems to interact with one another. For instance, a message communicated by a human to an AI agent may lead that agent to interact with a chatbot in order to produce a response that fits the user's request. At the same time, the chatbot that replies to the AI agent has also been guided by instructions from another human about how it should handle the information it receives.

Two main models of communication emerge from these roles. In the first, the Human–AI–Human model, a single chatbot or agent mediates the exchange between a user and a system. In the second, the Human–AI–AI–Human model, a user-facing chatbot draws on another AI system or agent before returning a response. This arrangement signals the growing presence of AI-to-AI interaction and shows that communication now extends beyond a closed loop between one person and one system, operating instead within a wider network of interacting actors. Evidence for this configuration appears across domains. Han et al. (2025) show that educational companion agents rely on separate learning-analytics engines that interpret multimodal inputs before the companion agent produces feedback. Zeng and Gupta (2025) describe a dual-agent orchestration model in which one agent manages workflow logic while another executes service delivery. Real-world systems, such as Perplexity's integration with OpenTable or Google's AI Mode linking directly to reservation infrastructures, further demonstrate how multiple AI systems coordinate to shape a single user-facing response. These examples collectively ground the Human–AI–AI–Human model in empirical observation rather than conceptual extension alone.

These findings link back to early work on Computer-Mediated Communication (CMC), which presented technology as a neutral channel within a Human–Computer–Human model. Sproull and Kiesler (1986) showed that electronic mail reduced important social cues while Walther (1996) argued through the *hyperpersonal model* that people could still form strong relationships by managing how they presented themselves. In this body of work, the computer influenced the flow of messages without acting as an independent participant. As AI-Mediated Communication (AI-MC) developed, technology began to take on more active roles. Hancock et al. (2020) demonstrated that AI systems can organise, guide, and shape interaction processes. The present review extends this shift by identifying two recurring configurations: the Human–AI–Human model, in which a single system manages exchanges with users, and the Human–AI–AI–Human model, in which several AI systems work together before returning a response. This empirical grounding clarifies a theoretical progression: communication infrastructures now embed multiple non-human actors whose coordinated operations cannot be captured by dyadic models alone.

Actor-Network Theory (ANT) offers a way to understand the roles of chatbots and agents within communication networks. Rather than treating agency as a fixed property, ANT describes it as something that develops through relationships between humans and technological systems. From this viewpoint, chatbots function as micro mediators that translate user input into system responses, while more advanced agents act as macro coordinators that draw together data sources, protocols, or services. These dynamics show that AI systems operate as more than technical instruments. They influence communication by shaping how messages are produced, circulated, and interpreted. Belliger and Krieger (2014) describe this as hybrid agency, in which human and non-human actors share responsibility for outcomes. The findings of this review suggest that AI-to-AI interaction exemplifies this form of agency, as systems collaborate with each other before returning information to users. The findings of this review illustrate ANT's notion of delegation: analytic engines in education, triage systems in healthcare, and workflow coordinators in public administration each perform interpretive work before communicative output is generated. AI-to-AI interaction therefore represents not only technical integration but a redistribution of agency across linked non-human actors, stabilising communication through interdependent processes.

Across sectors, a consistent pattern emerges in how chatbots and agents divide communicative roles. In customer service, chatbots interact directly with customers, while agents draw on these exchanges to refine service plans. In healthcare, chatbots collect symptoms and agents link this information with medical records to support clinical decisions. In education, chatbots act as tutors for individual learners, and agents oversee learning pathways for groups of students. In companionship settings, chatbots provide emotional responses, and agents monitor user sentiment to adjust the interaction. In public services, chatbots respond to citizen enquiries, and agents coordinate data and administrative processes across offices. Across these examples, AI systems take an active part in shaping communication, functioning as actors that influence how messages are generated and organised rather than operating solely as technical tools. Viewed together, these examples demonstrate a cross-domain pattern of distributed agency in which communicative outcomes are co-produced by multiple systems operating sequentially or collaboratively. This relational configuration aligns with ANT's emphasis on heterogeneous networks and helps explain why the Human–AI–AI–Human model recurs in diverse institutional settings.

From a theoretical perspective, the study highlights how communication models have evolved over time. In early CMC research, interaction followed a Human–Computer–Human pattern in which computers served as neutral channels. With the rise of AI-Mediated Communication, this shifted toward a Human–AI–Human model, where AI systems mediated exchanges between users and digital platforms. The findings of this review suggest a further development: a Human–AI–AI–Human model in which AI systems also interact with one another before returning output to users. This progression broadens communication theory by positioning AI as an active participant within networks rather than a passive medium. The contribution of this review therefore lies in identifying a multi-layered communicative architecture that incorporates both visible and invisible AI actors, extending existing models by demonstrating how message production increasingly depends on coordinated inter-agent processes.

These insights raise important challenges for organisations and regulators. When chatbots and agents operate together, assigning responsibility for errors or bias becomes more complex. Oversight also needs to extend beyond individual systems, since communication now unfolds within networks made up of multiple interacting actors. For organisations, this shift calls for platforms that recognise AI as a co-communicator rather than a simple tool. For regulators, it requires frameworks that address transparency, accountability, and fairness across interconnected systems. For communication theory, it invites a reconsideration of who qualifies as a communicator within digital networks. In practice, understanding communication as a networked process suggests that interventions targeting single systems may be insufficient, as the locus of agency increasingly lies in chains of linked actors rather than in any individual AI model.

This review indicates that AI-Mediated Communication is moving from the use of simple tools toward the operation of complex systems. Chatbots function as micro mediators, and agents act as macro coordinators that also interact with one another. The progression from a Human–Computer–Human model to Human–AI–Human, and now to Human–AI–AI–Human, marks a significant shift in how communication is understood. AI now participates actively in the process and works alongside people to shape the networks through which communication takes place. By situating these developments within ANT, the review demonstrates how communicative agency is increasingly distributed across human and non-human actors whose combined operations structure the conditions under which interaction occurs.

The evidence base synthesised in this review presents several limitations. Many of the included studies, particularly conference papers, offer limited methodological detail and rely strongly on self-report measures. Outcome indicators also differ widely across sectors, which makes direct comparison difficult and reduces the consistency that can be drawn from the findings. For this reason, the themes identified here should be viewed as indicative patterns emerging from a diverse and uneven body of research rather than as definitive conclusions. The review process itself adds further constraints. The literature search was conducted collaboratively by all four authors using Mendeley Search as the primary discovery tool, although this platform does not disclose full information about its indexing sources. Relevant work in adjacent fields such as HCI, computational linguistics, behavioural AI, or public policy may therefore not have been captured. Screening was carried out through discussion-based consensus rather than independent parallel review, and no formal risk-of-bias tool was applied due to the heterogeneous nature of the study designs. These factors introduce potential subjectivity into study selection and synthesis and should be considered when interpreting the overall findings.

Conclusion

Computer-mediated communication was originally understood as a relatively simple pattern in which interaction occurred through a human–computer–human sequence. With the development of artificial intelligence, however, communication processes have become more complex. The presence of chatbots and AI agents demonstrates that computers have increasingly assumed the role of active actors within communication. This study shows that chatbots give rise to a human–AI–human communication model. While this model remains broadly comparable to classical CMC, the ability of AI systems to process information and generate responses positions them as active communicative actors rather than merely neutral media.

This pattern develops further with the involvement of AI agents, as multiple AI platforms are able to communicate with one another to process human input, exchange information, and subsequently deliver output to another human user. This configuration is described as the human–AI–AI–human model. Together, these two models illustrate the evolution of computer-mediated communication into what can now be understood as AI-mediated communication.

The increasing role of computers as active communicative actors can be explained through Actor–Network Theory (ANT). Across various sectors, AI-based chatbots actively manage and respond to information exchanged with humans. A common example is found in customer service, where chatbots receive user queries, process them, and provide responses based on organisational rules and predefined protocols. Similar patterns are evident in healthcare, education, social support, and public administration. In some cases, two AI actors interact with one another while mediating exchanges between humans, such as when an AI agent coordinates multiple instructions before interacting with a customer-service chatbot.

These developments carry significant implications for research, policymaking, and practice. Theoretically, they extend traditional models of computer-mediated communication by showing how systems once regarded as tools now operate as active participants in message interpretation. This shift raises concerns about bias in AI-based interpretation, which warrants further investigation. For policymakers, these changes call for new regulatory approaches to AI-supported communication. For organisations and service providers, they open new possibilities for service delivery and the design of more effective and responsive interaction systems.

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Conflict of Interest

The author(s) have declared that no competing interests exist.

Author Contribution Statement

A: Conceptualization, Methodology, Project Administration, Supervision, Writing – Original Draft Preparation. G.S: Data Curation, Literature Search, Validation, Writing – Review & Editing. RDA: Data Curation, Investigation, Visualization, Writing – Review & Editing. FF: Investigation, Validation, Writing – Review & Editing.

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Data Availability Statement

No analytic code, quantitative datasets, or publicly archived data collection templates were generated for this review. All extracted study characteristics, screening notes, and thematic synthesis materials are available from the authors upon reasonable request.

Ethics Statements

This study is based entirely on the analysis of previously published academic literature and did not involve any human participants, animal subjects, or primary data collection. Therefore, ethical approval and informed consent were not required for this study. The journal adheres to the ethical standards set by the Committee on Publication Ethics (COPE).

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Appendix A

List of Included Studies in the Systematic Review

No	Author(s)	Year	Title	Source	Classification
1	Al-Barrak, S. A. & Al-Alawi, A. I.	2024	The contribution of chatbot to enhanced customer satisfaction: A systematic review	ICETSIS 2024 (IEEE)	Review
2	Khneyzer, C.; Rebeiz, K. S.; Touma, J.	2024	A comprehensive review of economic and managerial factors: The implications of AI chatbots in customer relationship management	IGI Global (book chapter)	Review
3	Sofiyah, F. R.; Dilham, A.; Lubis, A. S.; Lubis, D.	2024	The impact of artificial intelligence chatbot implementation on customer satisfaction in Padangsidimpuan: Study with structural equation modelling approach.	Mathematical Modelling of Engineering Problems	Article
4	Mei, C. W.; Konar, R.; Kumar, J.	2024	The role of AI chatbots in transforming guest engagement and marketing in hospitality	IGI Global	Review
5	Christopher, Y.; Sundjaja, A. M.; Mulvono	2024	The role of AI chatbots on e-commerce platforms: Understanding its influence on customer trust and dependability	ICITDA 2024 (IEEE)	Article
6	Sun, G. & Zhou, Y.-H.	2023	AI in healthcare: Navigating opportunities and challenges in digital communication.	Frontiers in Digital Health	Review
7	Sharma, D.; Kaushal, S.; Kumar, H.; Gainder, S.	2022	Chatbots in healthcare: Challenges, technologies and applications.	AIST 2022 (IEEE)	Article
8	Khan, A.; Zeb, I.; Fang, S.	2025	Tracing the development and influence of chatbots in contemporary healthcare systems.	IGI Global (book chapter)	Article
9	Ramesh, G.; Deekshitha, P.M.G.; Tarun, M.	2025	Transforming healthcare: A comprehensive review of AI-powered chatbots impact and applications in healthcare services.	AIDE 2025 (IEEE)	Review

No	Author(s)	Year	Title	Source	Classification
10	Han, Y.; Hong, S.; Li, Z.; Lim, C.	2025	Defining and classifying the roles of intelligent learning companion systems: A scoping review of the literature.	TechTrends	Review
11	Er-Rafyg, A.; Zankadi, H.; Idrissi, A.	2024	AI in adaptive learning: Challenges and opportunities.	Springer (SCI)	Review
12	Merrill, K.; Kim, J.; Collins, C.	2022	AI companions for lonely individuals and the role of social presence.	Communication Research Reports	Article
13	Alotaibi, J. O.; Alshahre, A. S.	2024	The role of conversational AI agents in providing support and social care for isolated individuals.	Alexandria Engineering Journal	Article
14	Silayach, N.; Ray, R. K.; Singh, N. K.; Singh, A.	2025	When algorithms meet emotions: Understanding consumer satisfaction in AI companion applications.	Journal of Retailing and Consumer Services	Article
15	Mishra, A. K.; Tyagi, A. K.; Dananjayan, S.; Rawat, A.	2024	Revolutionizing government operations: The impact of artificial intelligence in public administration.	Scrivener Publishing (book chapter)	Article
16	Chen, T.; Gasco-Hernandez, M.	2024	Uncovering the results of AI chatbot use in the public sector: Evidence from US state governments.	Public Performance and Management Review	Article
17	Akakpo, A.; Gyasi, E. A.; Oduro, B.; Akpabot, S.	2025	Artificial intelligence (AI) and the future of information privacy: Expert viewpoints.	Journal of Global Information Management	Review
18	Burton, S. L.; Burrell, D. N.; White, Y. W.; Bessette, D. I.	2024	An in-depth qualitative interview: The impact of artificial intelligence (AI) on privacy challenges and opportunities.	IGI Global	Review
19	Nah, S.; Luo, J.; Joo, J.	2024	Mapping scholarship on algorithmic bias: Conceptualization, empirical results, and ethical concerns.	International Journal of Communication	Review
20	Skarzyńska, E.; Paliszkiewicz, J.; Dabrowski, I.; Mendel, M.	2025	Risks, failures, and ethical dilemmas of AI technologies and trust.	IGI Global	Review

No	Author(s)	Year	Title	Source	Classification
21	Zeng, Y.; Gupta, G.	2025	Reliable collaborative conversational agent system based on LLMs and Answer Set Programming.	arXiv	Article

Appendix B

PRISMA Flow Diagram of Study Selection