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Review Article

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Charting the evolution of human–machine communication: a systematic review of 25 years of empirical research

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Abstract

This study systematically examines trends and patterns in human–machine communication (HMC) research from 2000 to 2024. Based on a comprehensive screening of studies published in 28 communication and interdisciplinary journals and 2 foundational books, we analyzed 209 peer-reviewed articles based on their metadata, theoretical frameworks, research methods, technologies of interest, and research themes. The findings show steady growth in HMC scholarship following its formal recognition as a subfield with the establishment of the ICA Interest Group in 2019, continued reliance on social scientific research designs, and increasing interdisciplinary contributions. A BERTopic analysis identified 9 coherent research clusters, reflecting a gradual shift from robot-focused investigations toward a broader range of studies on virtual agents, chatbots, and generative AI. Overall, this review maps HMC's intellectual trajectory and highlights key directions for future theoretical, methodological, and interdisciplinary development. It also discusses the increasingly ambiguous boundaries of HMC given the growing use of large language models and the convergent spaces between HMC and AI-mediated communication.

Keywords human–machine communication, systematic review, generative AI, virtual agents, social robots, research trends, content analysis

In recent decades, artificial intelligence (AI) has garnered increasing attention from communication scholarship, as emerging technologies like social robots and virtual agents are integrated into our daily lives and designed to perform various social roles, such as personal companions, assistants, teachers, and decision makers. This dramatic expansion poses new opportunities and risks for technology users and leads to heated discussions within academia about the nature of technology. In response, a growing number of communication researchers advocate for the discipline to pay more attention to understanding the actual practices of increasingly lifelike and communicative media technologies and investigating people's interaction with them and their implications (Guzman & Lewis, 2020). Therefore, human–machine communication (HMC), which focuses on meaning-making among humans and machines (Guzman, 2018) and theory development and refinement related to the interactions between people and technology (Spence, 2019), has become an emerging field of communication research.

HMC originates from communication scholars' increasing efforts to better understand individuals' communications with robots, agents, and computers. At its core, HMC investigates questions of communication pertaining to technologies designed to serve as communicators (Guzman et al., 2023). What has remained foundational to the development of HMC is its sustained focus on communication itself: specifically, how people interpret, engage with, and respond to communicative technologies, as well as the broader individual, organizational, and cultural implications of these interactions (Fortunati & Edwards, 2020; Guzman et al., 2023).

HMC research is shaped by varying methodological and epistemological approaches as well as theoretical perspectives (Guzman & Lewis, 2020). For example, Spence (2019) suggested that replicating past studies of interpersonal communication and replacing a human with a machine can promote theory building. Gambino et al. (2020) sought to capture the changes in technology, technology users, and the way people interact with technologies. They proposed that humans not only use human–human scripts in HMC but also develop human–media scripts to interact with media agents. Lombard and Xu (2021) revisited and expanded the Computers Are Social Actors paradigm to the Media Are Social Actors (MASA) paradigm, which provides explanations for people's social responses to technologies based on evolutionary psychology literature. The MASA paradigm sought to distinguish the effects of individual social cues

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and provided testable propositions for future scholars to test. Beyond these works, as Kuhn (2012) noted, a field that is developing to a mature level should be able to build conceptual frameworks or paradigms that integrate existing fragmented findings to guide the field's research. Therefore, to gain a comprehensive understanding of the HMC development, we conduct a systematic review to map its intellectual foundations and status quo, while also providing directions for future research endeavors.

This systematic review addresses several key gaps in the current literature. First, most existing trend studies on communication technologies have focused on research published in the 1990s and early 2000s (e.g., Borah, 2017; Khang et al., 2012; Taipale & Fortunati, 2014; Tomasello et al., 2010). In contrast, reviews of technology research conducted over the past two decades, a period marked by rapid technological advancement and profound societal shifts, remain underexplored. In particular, the 2010s have been recognized as a pivotal decade during which AI, automation, and immersive media technologies rapidly evolved and became integrated into everyday life (Auxier et al., 2019).

Second, HMC was introduced as a rising area at a Blue Sky workshop at the International Communication Association (ICA) in 2015 and subsequently institutionalized through the formation of the Human–Machine Communication Interest Group within ICA in 2019 (Guzman et al., 2023). Historically, the period from 2000 to 2018 was a formative stage in which AI-oriented technologies (e.g., computer agents, chatbots, smart speakers, and voice assistants) were gradually introduced and pertinent research began to take shape. In contrast, the years from 2019 to 2024 reflect a phase of intensified scholarly engagement and field consolidation. Therefore, examining the literature across this 25-year span, divided into pre- and post-2019 periods, presents a unique opportunity to trace the emergence, evolution, and expansion of the field of HMC since its formal recognition.

Third, although recent years have produced several valuable reviews of HMC, including bibliometric trend analyses (e.g., Makady & Liu, 2022; Richards et al., 2022) and agenda-setting works (e.g., Guzman & Lewis, 2020), our study adopts different scopes, search strategies, and analytic focuses. For example, Richards et al. (2022) examined communication-specific journals and covered research from 2011 to 2021, a period that might only have partially captured the transformative developments associated with LLMs and generative AI. Makady and Liu's (2022) trend analysis used broader keywords, including human–computer interaction and human–robot interaction to generate topic-level insights, which might have overlooked the work that explicitly engages with the HMC scholarship. Comparatively, this review analyzes peer-reviewed empirical studies published between 2000 and 2024 across a multilevel corpus of journals, including top-tier communication journals, interdisciplinary journals centered on emerging media and human–technology interaction, and classic HMC books. This review adopts replicable inclusion criteria that focus only on empirical studies explicitly using the term "human–machine communication" in titles, abstracts, keywords, or full texts, which enables us to map how HMC has emerged, consolidated, and come to define itself as a distinctive self-identified scholarly area. It reveals how researchers label and conceptualize their work when they intentionally situate their studies within the HMC space.

Guided by these goals, this review seeks to answer the following overarching questions: (a) How has HMC been theorized over the past 25 years, and what theoretical frameworks have been used in the field? (b) What types of technologies have been examined as communicators, and how have these technological foci evolved from 2000 to 2024? (c) What disciplinary, institutional, and geographic affiliations characterize the field's development? (d) What empirical methods have HMC scholars employed, and how have methodological preferences shifted over time? (e) How have the topical priorities and research questions within HMC scholarship evolved, and what themes define the field's intellectual trajectory? By integrating these analyses, this review provides a holistic assessment of HMC's historical trajectory and current landscape.

Literature review

History, evolution, and scope of HMC

Research on HMC is both old and new (Guzman, 2018). It is considered *old* because research on the intersections of humans and technologies has evolved in various fields such as human–computer interaction (HCI), engineering, computer science, information science, and computer-supported cooperative work (CSCW). Specifically, research on the intelligence of technology can be traced to the early 1950s, when Turing (1950) proposed the imitation game and postulated that if a machine tricks a human interrogator into believing that the machine is a person, then the machine can be considered intelligent. It was also during that time that Engelbart (1962) and Licklider (1960) contemplated how users could rely on computer interfaces to externalize their mental models.

Since then, different forms of thought experiment have inspired researchers to ponder over machine agency and intelligence. Searle's (1980) Chinese Room argument indicated that a computer's presentation of human language cannot be equated with its real understanding of the language. Suchman (2007) followed the inquiry into machine intelligence in her book *Human–Machine Reconfigurations*, pointing out that humans' meaningful interactions with machines must account for "specific local contingent determinants" (p. 84).

While today's HMC research has been informed and influenced by these thought experiments, scholars from other areas have also participated in discussions about human–technology relationships. For instance, science and technology studies (STS) researchers, such as Pinch and Bijker (1987), have proposed the social constructivism of technology (SCOT), arguing that knowledge of technology is socially and culturally constructed. Departing from SCOT, Winner (1980) cast light on the political implications of machines and suggested that, while the invention, design, or arrangement of machines has political consequences, machines themselves can be inherently political and engender power relations. Moreover, in Latour's (1992) actor-network theory, machines have their agency in influencing social networks just as humans do. Beyond STS, research centering on medium theories, cultural studies, critical studies, and information and communication technologies (ICTs) has also contributed to the conceptualizations of machines and affected communication scholars' perspectives (e.g., Gillespie et al., 2014; Lievrouw & Livingstone, 2006; Marvin, 1990; McLuhan & Fiore, 1967; Rogers, 1986).

Like the aforementioned areas, HCI research has also explored and parsed out human–technology relationships. Defined as "a discipline concerned with the design, evaluation, and implementation of interactive computing systems for human use and with the study of major phenomena surrounding them" (Hewett et al., 1996, p. 5), HCI research has spanned user experience (Gaver, 1991; Gibson, 1979; Norman, 1988), users' attitudinal and behavioral responses (Fogg, 2002; Rogers, 2012), and embodied interactions with various computing technologies (Dourish, 2006; Sirkin & Ju, 2014). Contemporary HCI research has further evolved into conversations about ubiquitous computing (Weiser, 1991), social computing (Schuler, 1994), affective computing (Picard, 2003), explainable AI (Liao et al., 2020), and accountable AI (Nushi et al., 2018).

The development of HCI research in the field of *communication* can be traced to two threads. The first thread focused more on the affordances of technology interfaces, especially how different interface cues affect users' trust and behavioral intentions (Lee & Sundar, 2010). The second thread focused more on how users perceive and respond to computer technologies as if they were social actors (Reeves & Nass, 1996). Nass et al. (1994) proposed the CASA paradigm and concluded that individuals apply social scripts to their interactions with computers, especially when computers demonstrate social dimensions such as voices and personalities. The findings related to CASA were later described as the Media Equation (Reeves & Nass, 1996), which has been used as a framework in research on social robots, chatbots, and computer agents (e.g., Edwards et al., 2014; Küster et al., 2021; Lee et al., 2006; Xu et al., 2025).

HMC is considered *new* because it has been gradually taking shape in communication in recent years (Guzman, 2018). While previous research on communication and technology has primarily focused on the mediating role of technology in human communication, a range of emerging technologies now serve as more than a medium or a channel (Gunkel, 2012; Guzman & Lewis, 2020). For example, Zhao (2006) conceptualized humanoid social robots not as channels for human communication but as entities with which humans interact. In addition to humanoid social robots, people increasingly form deep emotional connections, including friendship and romantic love, with AI companions (e.g., Replika) and large language models (LLM) (e.g., ChatGPT) (Banks, 2024; Kim et al., 2023; Li & Zhang, 2024). Another example would be the distinction between communication with avatars versus agents. Research on the former mode is considered mediated communication because avatars are controlled by human users, whereas research on the latter mode is considered HMC because agents are autonomous and algorithm-driven (Fox et al., 2015). In the HMC process, "the machine has become a communicative subject, and it is the subjectivity, rather than interactivity, that marks the technological transition" (Guzman, 2018, p. 12).

While the general boundaries of HMC have yet to coalesce, definitions of HMC have been provided (for more definitions, see Table 1). The journal *Human–Machine Communication* specifies that HMC involves:

> the theory and practice of communication with and about digital interlocutors, which may take the form of artificial conversation entities, artificially intelligent software, embodied machine communicators (robots), and technologically augmented persons (cyborgs), as well as on communication in the context of machine spaces (virtual and augmented realities) and human–machine configurations.

The research topics related to HMC inevitably overlap with some research on HCI, information science, and other areas. However, the distinctive feature of HMC is that scholars focus on the "communication" aspect and the meaning-making process among humans and machines (Guzman, 2018). Moreover, the usage of "machine" highlights not only the importance of including communicative technologies but also the ontological divides between humans and machines, including the differences in origin of being, degree of autonomy, status as tool versus tool-user, intelligence, and emotional capacity (Guzman, 2020). Overall, HMC is not a competitor to HCI, human–robot interaction (HRI), or human–agent interaction (HAI); it subsumes the portions of these areas that focus on technologies as communicative subjects (Guzman, 2018).

Table 1 Definitions of HMC.

Source	Definition
Human-Machine Communication Journal (2025)	HMC focuses on the theory and practice of communication with and about digital interlocutors, which may take the form of artificial conversation entities, artificially intelligent software, embodied machine communicators (robots), and technologically augmented persons (cyborgs), as well as on communication in the context of machine spaces (virtual and augmented realities) and human–machine configurations.
Human-Machine Communication ICA Interest Group (2025)	HMC refers to communication between people and technologies designed to enact the role of communicator, such as artificial intelligence (AI), robots, digital assistants, smart and Internet of Things (IoT) devices. HMC encompasses the aspects of Human–Robot Interaction (HRI), Human–Agent Interaction (HAI), and Human–Computer Interaction (HCI) pertaining to technologies that function as communicators.
Guzman (2018)	Human–machine communication comprises the study of the creation of meaning among people and machines and aspects thereof and is inclusive of the different philosophical, theoretical, and methodological approaches within the discipline.

Although the HMC scholarship features machines as communicative subjects and emphasizes the meaning-making process, it is important to maintain ongoing conversations about the boundaries of HMC. For example, AI-mediated communication may allow machines to serve as both mediators and interlocutors (Hancock et al., 2020). Human experts may be included in the loop of machines' data training and outcome verification processes, making algorithmic recommendations more transparent and trustworthy (Xu & Shi, 2024). Although these developments blur the boundaries of HMC, they allow scholars from different fields to collaborate and investigate the new frontiers of HMC. Therefore, although it is feasible to identify the core distinctions between HMC and other areas, such as HCI, HAI, and HRI, keeping the discussion about the boundaries of HMC open may engage more interdisciplinary collaboration and allow HMC scholars to both absorb insights from other areas and provide novel theoretical perspectives in return.

HMC has been taking its own turn toward becoming independent in the discipline of communication. Initial efforts toward this step include the BlueSky workshop at the 2015 International Communication Association (ICA) in Puerto Rico, the post-conference at the 2016 ICA in Fukuoka, Japan, and the succeeding pre-conferences at the annual conferences of ICA, including ones in Paris, Toronto, and Denver. In 2019, HMC became an official interest group at ICA. In 2026, it became a division of ICA.

Moreover, several workshops and panels have been held at the *ACM/IEEE International Conference on Human–Robot Interaction* and the *Association of Internet Researchers* (AoIR). With regard to journals, scholars incorporated special HMC issues in the journals like *Computers in Human Behavior* and *Media Culture, and Society*, and launched the journal *Human–Machine Communication* in 2020. Guzman et al. (2023) published the *Sage Handbook of Human–Machine Communication*, which introduces the histories, methods, contexts, and applications in this academic space.

The theoretical and methodological needs for a systematic review

Given these efforts, the theoretical frameworks and methodological approaches in the HMC field have been witnessing ongoing progress over the past decade (Fortunati & Edwards, 2020). In terms of theory, on the one hand, many concepts and theories from various disciplines, such as theories of presence (Lombard et al., 2017), mind perception (Gray et al., 2007), and anthropomorphism (Epley et al., 2007), have addressed essential questions in HMC (Spence, 2019). Existing interpersonal theories, computer-mediated communication theories (e.g., social information processing theory) (Walther, 1996), and HCI theories (e.g., activity theory) (Nardi, 1996) have also been tested and extended in HMC. On the other hand, theories central to HMC are being continually tested, refined, and developed. For example, the evolution of machines from computers to more diverse artifacts calls for a need to advance theories to investigate the human communication process with those machines. Indeed, scholars addressed those changes by revisiting and expanding the CASA paradigm to include human communication with artifacts beyond computers (e.g., Gambino et al. 2020; Lombard & Xu, 2021). As Spence (2019) suggested, a starting assumption for developing HMC theories is that HMC is more than just examining communication devices or human support; it involves open conversations and strengthening the case for HMC being treated as a distinct field.

The methodological approaches used in the HMC field have also made significant progress. There is growth in the employment of qualitative and mixed-method approaches beyond quantitative designs (Fortunati & Edwards, 2021). While quantitative approaches have been identified as the predominant methods in prior trend analyses and systematic reviews (see Khang et al., 2012; Taipale & Fortunati, 2014; Zhang & Leung, 2015), more diverse methodological approaches have been encouraged to investigate various phenomena related to emerging technologies (Kim et al., 2017). For example, Spence (2019) noted that it would be heuristically provocative for HMC scholars to replicate classic studies using observational methods. Fortunati and Edwards (2021) suggested that it is encouraging to see critical approaches to HMC emerge and "challenge more traditional and administrative approaches to theory and practice" (p. 23).

The disciplinary and institutional needs for a systematic review

HMC has attracted scholars from various disciplines, including communication, psychology, anthropology, information science, engineering, business, HRI, and HCI (Edwards et al., 2021). To map out the future paths of HMC, Fortunati and Edwards (2021) argued that interdisciplinarity is crucial for constructing this new field because no single theoretical or methodological approach can offer a full understanding of the processes and consequences of HMC.

Scholars have also analyzed the institutional factors endemic to the HMC field. Guzman (2018) mentioned that the study of HMC has been fractured since its initial formation: many communication researchers who study human interactions with technology conduct research and submit manuscripts outside of the communication discipline. Since there was no commonly defined scholarly space to gather communication scholars to engage in conversations, HMC emerged as a field to provide a shared conceptual and institutional space for examining communication with machines. As consensus grows that HMC is an interdisciplinary field, a comprehensive review of existing scholarship is needed to understand how the field has taken shape and to support deeper cross-disciplinary engagement.

Although HMC scholarship has grown steadily over the past decade, particularly following the establishment of the HMC Interest Group in 2019, it remains unclear how the field has evolved along these different dimensions over time, where it currently stands, and how it is positioned to develop in the future. Systematic reviews are particularly well-suited for mapping a field's intellectual structure by identifying dominant theoretical approaches, methodological patterns, and disciplinary contributions (Borah, 2017; Fu & Lai, 2020; Tomasello et al., 2010; Ye & Ki, 2012). To address this gap, the present study conducts a comprehensive and protocol-driven review of empirical HMC research published between 2000 and 2024. Specifically, we propose the following research questions:

RQ1a: What have been the major theories used in HMC research?

RQ1b: How have the theories featured in HMC research evolved over time?
RQ2a: What types of technologies have been investigated in HMC research?
RQ2b: How have the technologies studied in HMC research evolved over time?
RQ3a: What is the disciplinary distribution of published HMC research?
RQ3b: How has the disciplinary distribution changed over time?
RQ4a: What major research methods have been applied in HMC research?
RQ4b: How have the methods applied in HMC research evolved over time?
RQ4c: How are research methods associated with different technologies and disciplinary affiliations in HMC research?
RQ5a: What topical themes have been covered in empirical HMC research?
RQ5b: How have the topical themes in HMC evolved over time?

Methods

Study identification and inclusion

The research population of this study consisted of empirical research on HMC published between January 2000 and December 2024. A total of 209 peer-reviewed empirical articles were identified through a comprehensive screening of 28 scholarly journals and two foundational books. To accurately map HMC as a scholarly field, we used the exact term "human–machine communication" across article titles, abstracts, keywords, and full texts. This keyword-based approach was necessary for identifying scholarship in which authors intentionally frame, label, or position their work within the HMC space. It also reflects the goal of our study, which is to map how the HMC scholarship has emerged, consolidated, and become a self-identified research area over time.[1] The articles were collected in early 2025.

Specifically, following established practices in systematic reviews of emerging communication technologies (e.g., Borah, 2017; Kim et al., 2017; Taipale & Fortunati, 2014), we adopted a multilevel sampling strategy. The first group consisted of top-tier communication journals, specifically those ranked in the first and second quartiles of the 2023 Clarivate Journal Citation Reports (SSCI and ESCI indexed) within the Communication category. The second group comprised interdisciplinary journals focused on emerging media and human–technology interaction, such as *Computers in Human Behavior*, *International Journal of Human–Computer Studies*, and *Telematics & Informatics*. The third group included two foundational books widely recognized for shaping the HMC field: *Human–Machine Communication* (Guzman, 2018) and the *SAGE Handbook of Human–Machine Communication* (Guzman et al., 2023). A complete list of sources is provided in the Supplementary Appendix. Additional searches were conducted in major academic databases, including EBSCOhost, Web of Science, ScienceDirect, APA PsycNet, and Google Scholar, to ensure a comprehensive coverage of qualified studies.

The search strategy was applied to all 28 journals and two books, with a total of 2,357 articles identified. Afterward, duplicates ($n = 1{,}112$) were removed. We then reviewed the abstracts and full texts of all remaining articles ($n = 1{,}245$) to determine whether they met the inclusion and exclusion criteria. To be eligible for inclusion, articles were required to meet all of the following criteria: (a) explicitly use the term "human–machine communication," (b) fall within the conceptual scope of HMC based on established definitions (see Table 1), and (c) be published in English. In assessing conceptual fit, we referred to definitions and topics listed in prior HMC-related conference calls (e.g., ICA HMC interest group call for paper and ICA HMC preconference call for paper) and manually checked whether the goals, research questions, or analyzed phenomena were related to direct communication between users and technologies.

Meanwhile, the following exclusion criteria were used. First, articles from engineering or computer science that focused solely on the development of a hardware or software system, which did not examine human factors were excluded. For example, research that introduced an algorithm but did not examine its effects on users was excluded. Second, we excluded non-empirical studies, which consisted of (a) review articles that used systematic reviews or meta-analysis, (b) conceptual or theoretical papers without empirical evidence, and (c) editorial statements. In other words, studies without empirical evidence were excluded. Third, articles that examined technologies as mere mediators were excluded.

Based on these criteria, we excluded 928 articles based on their abstracts and then manually assessed 317 full-text papers for their eligibility. A total of 108 full-text articles were further excluded. The final sample consisted of 209 empirical articles, which served as the basis for this systematic review. These steps reflect a loose opt-in, tight opt-out approach: we cast a broad net by searching the exact term across multiple text fields and then applied conceptual and empirical screening criteria to narrow down the corpus. The screening and selection process followed the PRISMA guidelines (Page et al., 2021) and is illustrated in Figure 1.

Coding scheme

Drawing on the coding schemes used in previous trend studies (e.g., Khang et al., 2012), we identified an initial set of coding variables such as research methods and theoretical frameworks. We included additional coding variables, such as the first authors' disciplinary affiliations and the technologies studied in HMC. We then determined the specific values by referring to previous longitudinal analyses of published articles (e.g., Kim et al., 2010, 2014; Ye & Ki, 2012). In this process, we incrementally updated our initial coding scheme as new cases emerged that

[1] We recognize that many studies in adjacent areas such as HCI, HRI, and HAI examine phenomena closely related to human–machine communication without explicitly using the HMC label. Including these studies would broaden the corpus but could also introduce greater conceptual heterogeneity, making it more difficult to distinguish HMC as a self-identified research field and to draw coherent conclusions about its intellectual development. This approach may also reduce the replicability of the review, as inclusion decisions would rely more on interpretive judgment than on explicit self-designation. For these reasons, we focus on scholarship that intentionally frames itself as HMC.

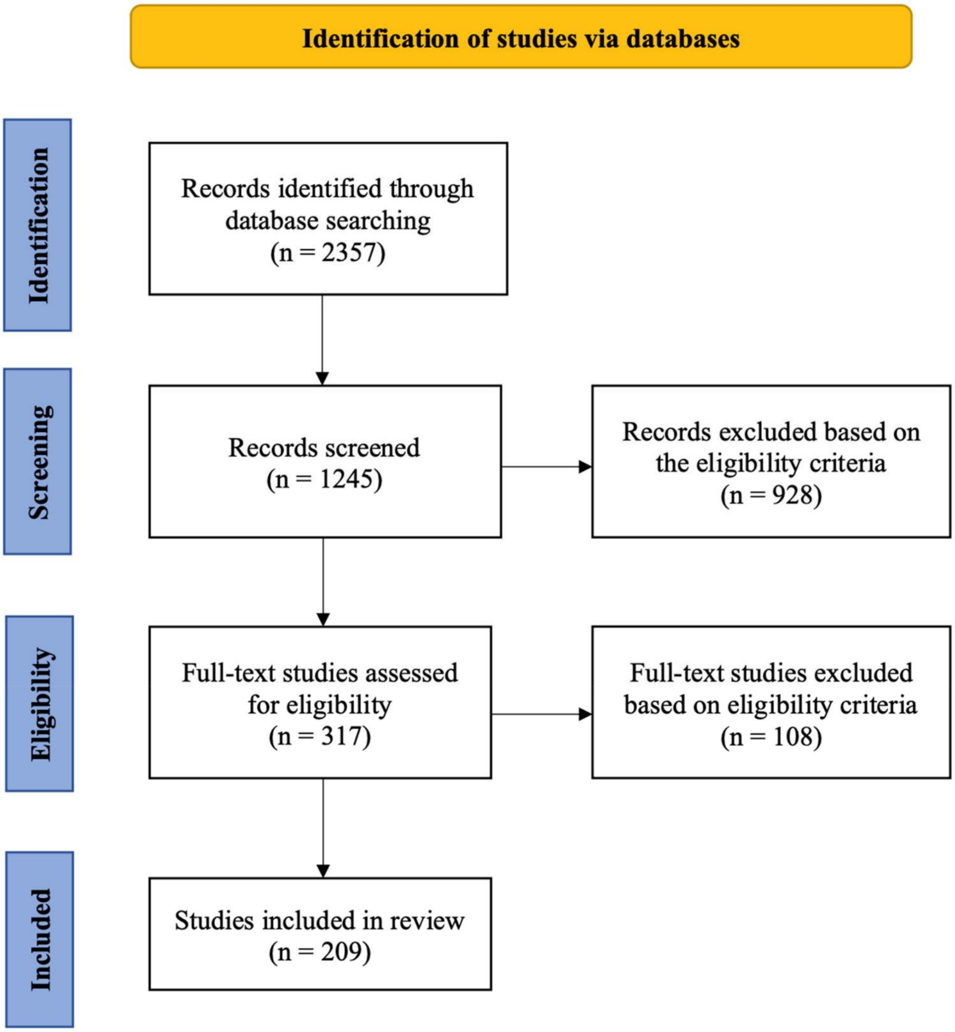

Figure 1 PRISMA diagram of sample selection process.

did not fit into the earlier scheme until all possible cases were addressed. The final scheme adhered to a mutually exclusive and exhaustive structure (Kim et al., 2010).

We coded each article based on four major dimensions: (a) general information about the publication, including journal/book name, year, the location where the study was conducted, and the first author's discipline affiliation, (b) theoretical frameworks, (c) technologies of interest, and (d) research methods. The coding scheme can be accessed in the Supplementary Appendix.

General information

We coded each article based on the journal/book it was published and its year of publication. We also coded the geographic location of the study and the disciplinary affiliation of the first author (e.g., communication, engineering, business) to understand the international scope and interdisciplinary collaborations among HMC research.

Theoretical framework

We coded the theoretical frameworks applied or tested in the articles based on whether an article explicitly referenced a theoretical framework. If a specific theory was identified, its name was coded. This allowed us to track the frequency and evolution of theoretical grounding within the field.

Research method

Adapted from previous research (Lee, 2017; Trumbo, 2004), we categorized each article by its primary methodological approach. Method types included, but were not limited to, experiments, surveys, physiological measures, interviews, discourse analysis, and mixed methods.

Technology in HMC

To classify the technologies examined in the included studies, we coded each technology according to its communicative roles in the article. Specifically, we assessed whether the technology functioned as a communicative subject in the interaction. Based on this principle, we organized the technologies into five categories: physical robots, virtual agents, smart/IoT devices, algorithm/AI-generated content/generative AI, and other technologies. The detailed coding criteria and examples for each category are presented in the Supplementary Appendix. However, it should be noted that recent technological convergence, particularly the integration of LLMs across conversational agents, smart devices, and platform infrastructures (Natale, 2023), has made it increasingly challenging to maintain strictly mutually exclusive category boundaries. Accordingly, we analyzed each case individually and assigned categories based on how the study conceptualized the technology's role in the communicative process. These distinctions are therefore primarily functional and study-based rather than strictly ontological.

Intercoder reliability

Following Lombard et al.'s (2002) steps of conducting content analysis, after the coding book was established, two researchers independently coded 42 randomly selected articles (i.e., 20% of all the selected articles) to test intercoder reliability. Using Krippendorff's alpha (2018), the intercoder reliability reached 1.0 for general information (journal name, publication year, research location, and the first author's disciplinary affiliation), 0.87 for theoretical frameworks, 0.92 for research methods, and .96 for types of technologies. The overall intercoder agreement was 0.95. According to Lombard et al. (2002), for the coding of a variable to be considered reliable, Krippendorff's alpha needs to be 0.70 or higher. Therefore, the intercoder reliability of all the variables in this study was acceptable. Then the two coders independently coded half of the remaining articles.

BERTopic analysis

To map the major research themes represented across HMC scholarship, we conducted a topic modeling analysis using BERTopic on the titles and abstracts of the reviewed articles. For each study, the title and abstract were concatenated and preprocessed following standard natural language processing procedures, including tokenization, lemmatization, stopword removal, and low-frequency term filtering. The preprocessed texts were then transformed into dense semantic embeddings using a pretrained sentence-BERT model and subsequently reduced in dimensionality using UMAP to facilitate stable clustering.

BERTopic applies hierarchical density-based spatial clustering of applications with noise (HDBSCAN) to identify coherent clusters of semantically similar documents and extracts representative keywords for each cluster using class-based term frequency–inverse document frequency (c-TF-IDF). We explored alternative parameter settings and selected the model that achieved the optimal balance between topic coherence and interpretability (coherence = 0.506; *n*_components = 10; *n*_neighbors = 20; min_cluster_size = 5). Documents assigned to the outlier cluster were examined during model refinement, and topic-level outputs were generated based on the final set of documents assigned to interpretable thematic clusters.

Two authors independently reviewed the top keywords and representative documents for each cluster and reached full agreement on final topic labels: (a) AI teachers and education, (b) AI journalism and news automation, (c) voice assistants and genders, (d) chatbots and social disclosure, (e) trust in machines' decision-making, (f) digital identity, privacy, and autonomy, (g) social and mind perceptions of social robots, (h) social presence and relational development with virtual agents, and (i) social media engagement with virtual humans. Additional methodological details, complete keyword lists, and visualization outputs are provided in the Supplementary Appendix.

Results

A total of 209 empirical studies on HMC were identified and coded. Among these, the journal *Human–Machine Communication* accounted for the largest share in publishing empirical HMC studies (i.e., 39 articles, 18.7%), followed by *Computers in Human Behavior* with 29 articles (13.9%), and *International Journal of Human–Computer Interaction* with 20 articles (9.6%). Other leading publication outlets included *New Media & Society* (13 articles, 6.2%), *Journal of Computer-Mediated Communication* (12 articles, 5.7%), and *Digital Journalism* (11 articles, 5.3%). Table 2 presents the top 10 journals that published the most HMC-related articles during the review period. Overall, as shown in Figure 2, the volume of HMC research steadily increased from 2000 to 2024. Notably, over 88% of the reviewed articles were published after 2018, reflecting a marked acceleration in scholarly attention following the formalization of HMC as a research area.

Theoretical frameworks

RQ1a asked about the theoretical frameworks used in HMC studies. Our results showed that among the 209 articles reviewed, 153 (73.2%) explicitly mentioned a theoretical framework. As shown in Figure 3, we identified the top six frequently used theories: CASA/the Media Equation ($n = 58$, 37.9%), presence-related theories ($n = 15$, 9.8%), the Modality, Agency, Interactivity, and Navigability (MAIN) Model ($n = 11$, 7.2%), Theory of Mind ($n = 9$, 5.9%), the Technology Acceptance Model (TAM) ($n = 6$, 3.9%), and Actor-Network Theory ($n = 4$, 2.6%).

The frequency of applying these theoretical frameworks varied over the years (see Figure 4). CASA and the media equation have remained the dominant paradigms throughout 2000 to 2024. As shown in Table 3, CASA and the Media Equation, presence theories, and the MAIN model were the most frequently used frameworks both before and after 2018. Notably, Theory of Mind has gained traction only in recent years, with no studies employing it before 2018 and nine studies (9.1%) adopting it between 2019 and 2024.

RQ1b examined how the theories in HMC research evolved from 2000 to 2024. To assess the direction of this relationship,

Table 2 Top 10 journals with the most publications of HMC research.

Journal	Frequency	Percent
Human-Machine Communication	39	18.7
Computers in Human Behavior	29	13.9
International Journal of Human-Computer Interaction	20	9.6
New Media & Society	13	6.2
Journal of Computer-Mediated Communication	12	5.7
Digital Journalism	11	5.3
Behaviour and Information Technology	11	5.3
International Journal of Social Robotics	10	4.8
International Journal of Human-Computer Studies	7	3.3
Communication Studies	7	3.3

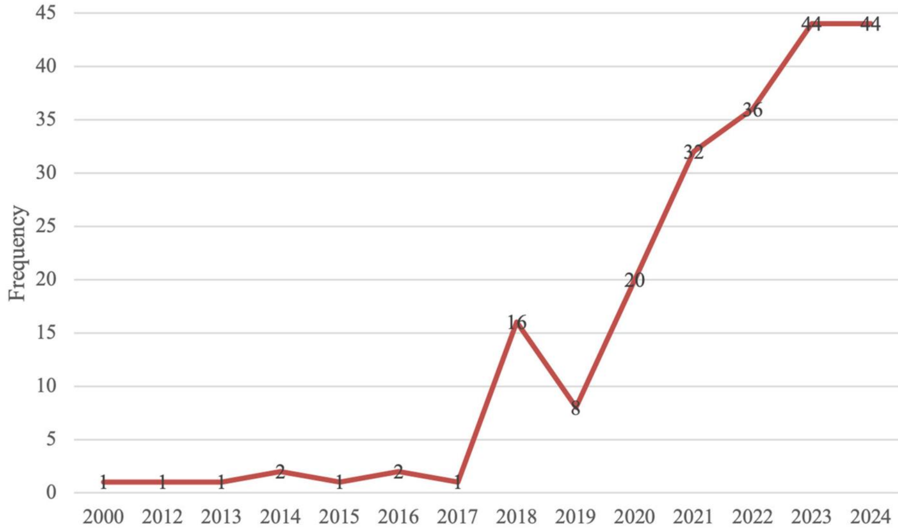

Figure 2 Trend of published HMC research from 2000 to 2024.

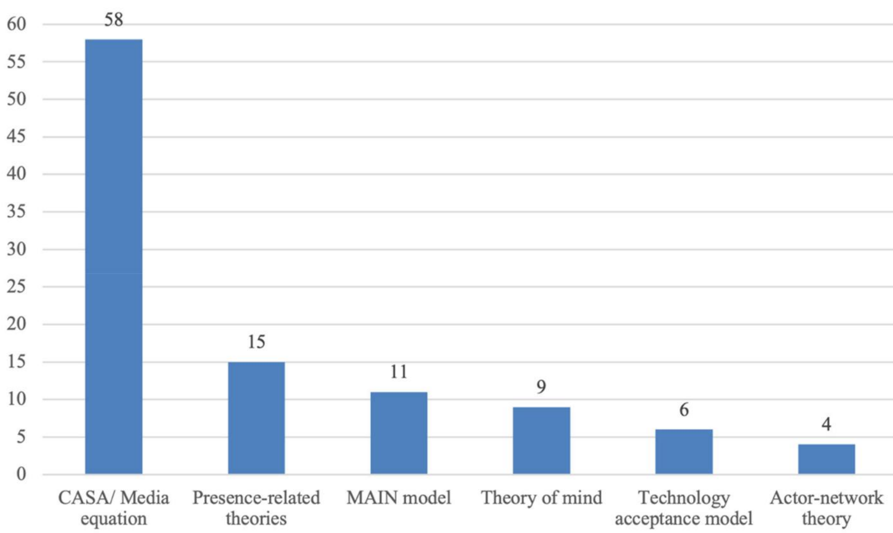

Figure 3 Frequently used theories in HMC research.

Pearson correlations were computed. Results indicated significant positive correlations between the year and the employment of the CASA/Media Equation, $r = 0.65$, $p = .011$; the MAIN model, $r = 0.58$, $p = .031$; and Theory of Mind, $r = 0.62$, $p = .018$. No other significant correlations were detected.

Technologies in HMC

RQ2a examined the types of technologies that have been investigated in HMC research. From 2000 to 2024, the most frequently studied technology was virtual agents ($n = 87$, 38.7%), followed by algorithm/AI-generated content/generative AI ($n = 57$, 25.3%), physical robots ($n = 51$, 22.7%), smart and IoT devices ($n = 26$, 11.6%), and other technologies ($n = 4$, 1.8%). To further understand how virtual agents were studied, we explored whether they were embodied agents, which are graphically rendered with visible bodies capable of conveying facial expressions or gestures (e.g., virtual influencers) (Tan & Liew, 2020), or disembodied agents, which interact via text or voice without visual embodiment (e.g., chatbots) (Araujo, 2018). Results showed that the majority of virtual agents were disembodied ($n = 58$, 66.7%), while 15.1% ($n = 13$) were embodied. Similarly, for studies involving physical robots, we examined whether the robots were studied in physically present contexts (e.g., face-to-face interaction with Robot NAO) or virtually present settings (e.g., observing robot behavior through video). Among the studies involving physical robots, 37.2% ($n = 19$) were physically present, and 33.3% ($n = 17$) used virtual representations.

As shown in Figure 5, longitudinal trends indicate steady growth in studies focusing on virtual agents, algorithm/AI-generated content/generative AI, and smart and IoT devices. At the same time, the distribution of technological focus shifted across periods. Table 4 demonstrates that, from 2000 to 2018, physical robots were the most frequently studied technology ($n = 10$, 37.0%), followed by virtual agents ($n = 9$, 33.3%) and algorithm/AI-generated content/generative AI ($n = 6$, 22.2%). Between 2019 and 2024, the

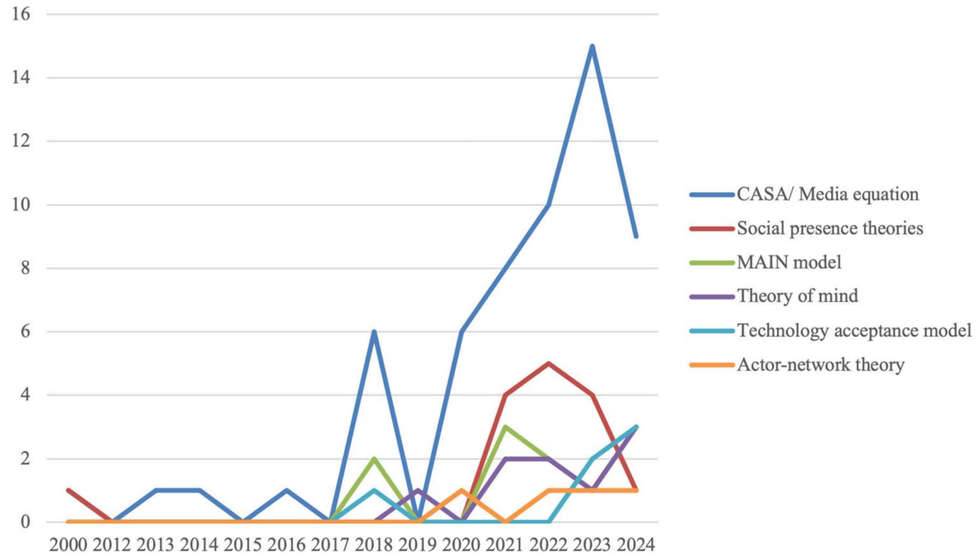

Figure 4 Trends of used theories in HMC research from 2000 to 2024.

Table 3 Theories used in HMC research before and after 2018.

	2000–2018		2019–2024		Total	
	n	%	*n*	%	*n*	%
CASA/media equation	10	62.5	48	48.5	58	37.9
Presence-related theories	1	6.3	14	14.1	15	9.8
MAIN model	2	12.5	9	9.1	11	7.2
Theory of mind	0	0	9	9.1	9	5.9
Technology acceptance model	1	6.3	5	5.1	6	3.9
Actor-network theory	0	0	4	4.0	4	2.6

Note. Among coded 209 HMC studies, a total of 153 explicitly employed theory.

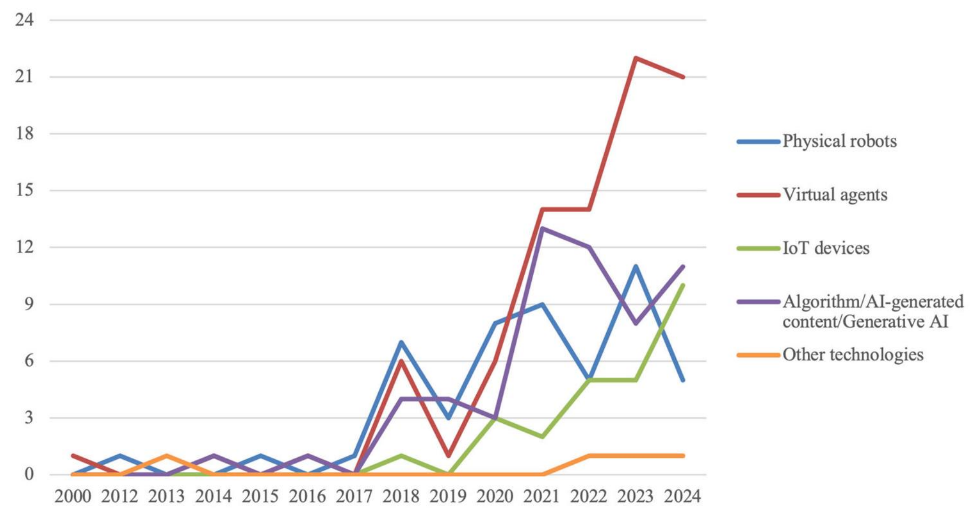

Figure 5 Technologies studied in HMC research from 2000 to 2024.

Note. Other technologies (n = 4) include aircraft machines, memory implants, and e-maps.

number of studies on physical robots continued to increase, yet their relative share (20.7%) declined. In contrast, virtual agents ($n = 78$, 39.4%) and algorithm/AI-generated content ($n = 51$, 25.8%) emerged as the dominant technologies.

To address RQ2b, correlations between publication year and technology type revealed significantly positive associations for physical robots, $r = 0.68$, $p = .007$; virtual agents, $r = 0.68$, $p = .008$; smart & IoT devices, $r = 0.64$, $p = .014$; and Algorithm/AI-generated

Table 4 Communicative technologies studied in HMC research before and after 2018.

	2000–2018		2019–2024		Total	
	n	%	*n*	%	*n*	%
Physical robots	10	37.0	41	20.7	51	22.7
Virtual agents	9	33.3	78	39.4	87	38.7
Smart and IoT devices	1	3.7	25	12.6	26	11.6
Algorithm/AI-generated content/generative AI	6	22.2	51	25.8	57	25.3
Other technologies	1	3.7	3	1.5	4	1.8

Note. Percentages are based on technology instances because some studies examined more than one type of technology.

Table 5 Disciplinary affiliation of the first author for HMC research before and after 2018.

	2000–2018		2019–2024		Total	
	n	%	*n*	%	*n*	%
Communication	19	79.2	136	73.9	155	74.2
Psychology	0	0	2	1.1	2	1.0
Engineering	0	0	3	1.6	3	1.4
Information	0	0	9	4.9	9	4.3
Computer science	2	8.3	9	4.9	11	5.3
Business	0	0	4	2.2	4	1.9
HCI research center	0	0	3	1.6	3	1.4
Others	3	12.5	19	10.3	22	10.5

content/Generative AI, $r = 0.70$, $p = .005$. These results confirm that all technology categories increased in frequency over time.

Disciplinary affiliations

RQ3a examined the disciplinary distribution of HMC research based on the first author's departmental affiliation. Results showed that the majority of publications came from scholars in communication ($n = 155$, 74.2%), computer science ($n = 11$, 5.3%), and information ($n = 9$, 4.3%). Table 5 presents the full lists. Communication has remained the dominant field throughout the review period, comprising 79.2% ($n = 19$) of studies between 2000 and 2018 and 73.9% ($n = 136$) between 2019 and 2024. While communication continued to lead the field after 2018, contributions from other disciplines have increased. Between 2019 and 2024, studies by scholars in information ($n = 9$, 4.9%) and computer science ($n = 9$, 4.9%) became more visible. As illustrated in Figure 6, this growing interdisciplinary engagement suggests an expanding scope for HMC research beyond its communication roots.

We also coded the geographic location of each study to assess the international scope of the field. Most studies were conducted in the United States ($n = 85$, 40.7%), followed by Germany ($n = 21$, 10.0%), China ($n = 18$, 8.6%), and studies conducted across multiple countries ($n = 10$, 4.8%).

To answer RQ3b, which sought to examine the evolution of discipline distribution over time, a series of Pearson correlation tests was conducted. Results indicated significantly positive correlations between the year and the studies carried out by the following affiliations: communication, $r = 0.74$, $p = .003$; information, $r = 0.55$, $p = .043$; and computer science, $r = 0.69$, $p = .006$. Studies from each of these disciplines saw significant growth across the years. No other significant correlations were detected.

Methods

RQ4a examined the major research methods employed in HMC studies. Results indicated that experiments were by far the most frequently used method ($n = 106$, 50.7%), followed by surveys ($n = 31$, 14.8%), interviews ($n = 19$, 9.1%), case studies ($n = 10$, 4.8%), and mixed methods ($n = 9$, 4.3%). The full list of methods is presented in Table 6. Quantitative research methods, especially experiments, have consistently dominated HMC research from 2000 to 2024. Notably, the use of both experiments and surveys increased substantially after 2019. To further explore the use of experiments, we coded whether they were conducted in person (lab-based) or online. The majority were conducted online ($n = 77$, 72.6%), while 22.6% ($n = 24$) were conducted in lab settings.

Although experiments remained the leading method, there was also a noticeable increase in studies using surveys ($n = 29$, 15.8%), interviews ($n = 17$, 9.2%), and case studies ($n = 10$, 5.4%) between 2019 and 2024. As shown in Figure 7, these trends reflect a gradual diversification of methodological approaches. While quantitative methods continued to dominate ($n = 143$, 68.4%), qualitative methods ($n = 46$, 22.0%) have gained greater prominence, especially in the years after 2018.

To address RQ4b, which examined how research methods evolved over time, Pearson correlation analyses showed significant positive associations between publication year and the use of both quantitative methods ($r = 0.74$, $p = .002$) and qualitative methods ($r = 0.73$, $p = .003$). Specifically, significant increases

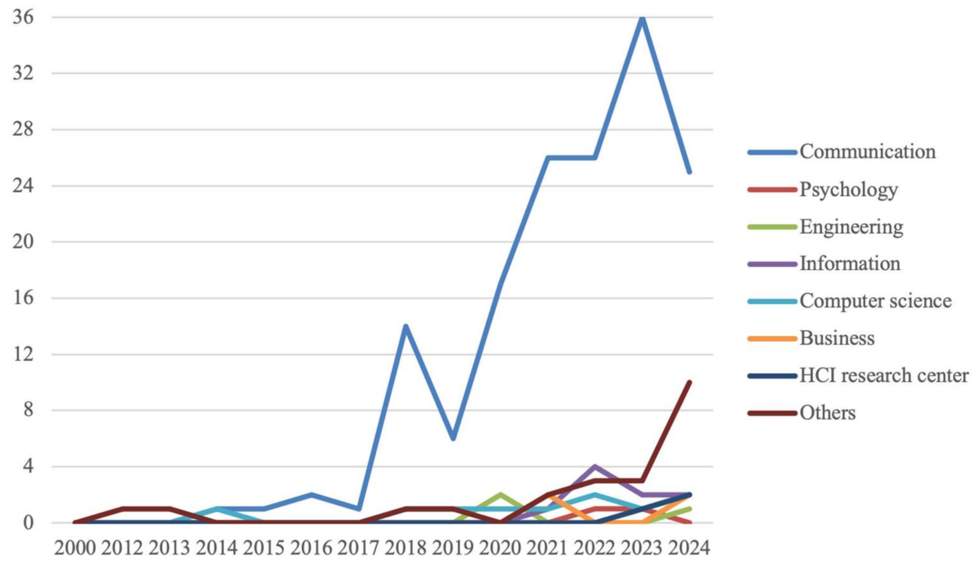

Figure 6 Trends of disciplinary affiliations in HMC research from 2000 to 2024.

Note. Others (n = 22) encompass humanities, psychosocial medicine, system design, intelligent manufacturing, agriculture, life sciences, tourism, community development, the state key laboratory of cognitive neuroscience and learning, and industries such as internet service companies and individualized production in architecture.

Table 6 Methods employed in HMC research before and after 2018.

	2000–2018		2019–2024		Total	
	n	%	*n*	%	*n*	%
Experiment	15	60.0	91	49.5	106	50.7
Survey	2	8.0	29	15.8	31	14.8
Content analysis	0	0	5	2.7	5	2.4
Mixed methods	1	4.0	8	4.3	9	4.3
Interview	2	8.0	17	9.2	19	9.1
Field/participant observation	1	4.0	5	2.7	6	2.9
Physiological methods	0	0	1	0.5	1	0.5
Computational methods	1	4.0	6	3.3	7	3.3
Case study	0	0	10	5.4	10	4.8
Focus group	0	0	2	1.1	2	1.0
Textual/image/video analysis	2	8.0	5	2.7	7	3.3
Discourse analysis	0	0	2	1.1	2	1.0
Others	1	4.0	3	1.6	4	1.9

over time were observed for studies using experiments ($r = 0.72$, $p = .004$), surveys ($r = 0.68$, $p = .008$), mixed methods ($r = 0.57$, $p = .034$), and interviews ($r = 0.66$, $p = .011$). RQ4c examined how methodological choices varied by technology type and disciplinary affiliation. Descriptively, experiments were most commonly used to study virtual agents ($n = 46$, 43.4%) and robots ($n = 29$, 27.4%). Surveys were primarily applied in research on virtual agents ($n = 11$, 35.5%) and algorithm/AI-generated content/generative AI ($n = 9$, 29.0%). Interviews were especially prominent in studies on algorithm/ AI-generated content/generative AI ($n = 9$, 47.4%). The relationship between methodological choice and disciplinary affiliation was not statistically significant, χ^2 (84, $n = 209$) = 76.06, $p = .719$, Cramer's $V = 0.21$, indicating that research method use was relatively consistent across disciplines.

Research topics

To address RQ5a and map the major thematic areas represented in HMC scholarship, we conducted a BERTopic analysis, which revealed nine coherent topics, summarized in Table 7. Figure 8 displays the relative prevalence of the nine topics. "Social and mind perceptions of social robots" is the most prevalent topic, reflecting the central role of social robotics in shaping early conceptual and empirical development in HMC, followed by "chatbots and social disclosure," "social media engagement with virtual humans," "voice assistants and genders," and "social presence and relational development with virtual agents," indicating that the field has expanded beyond physically embodied agents to include a wider range of virtual, voice-based, and conversational agents. Additionally, emerging areas such as "AI teachers

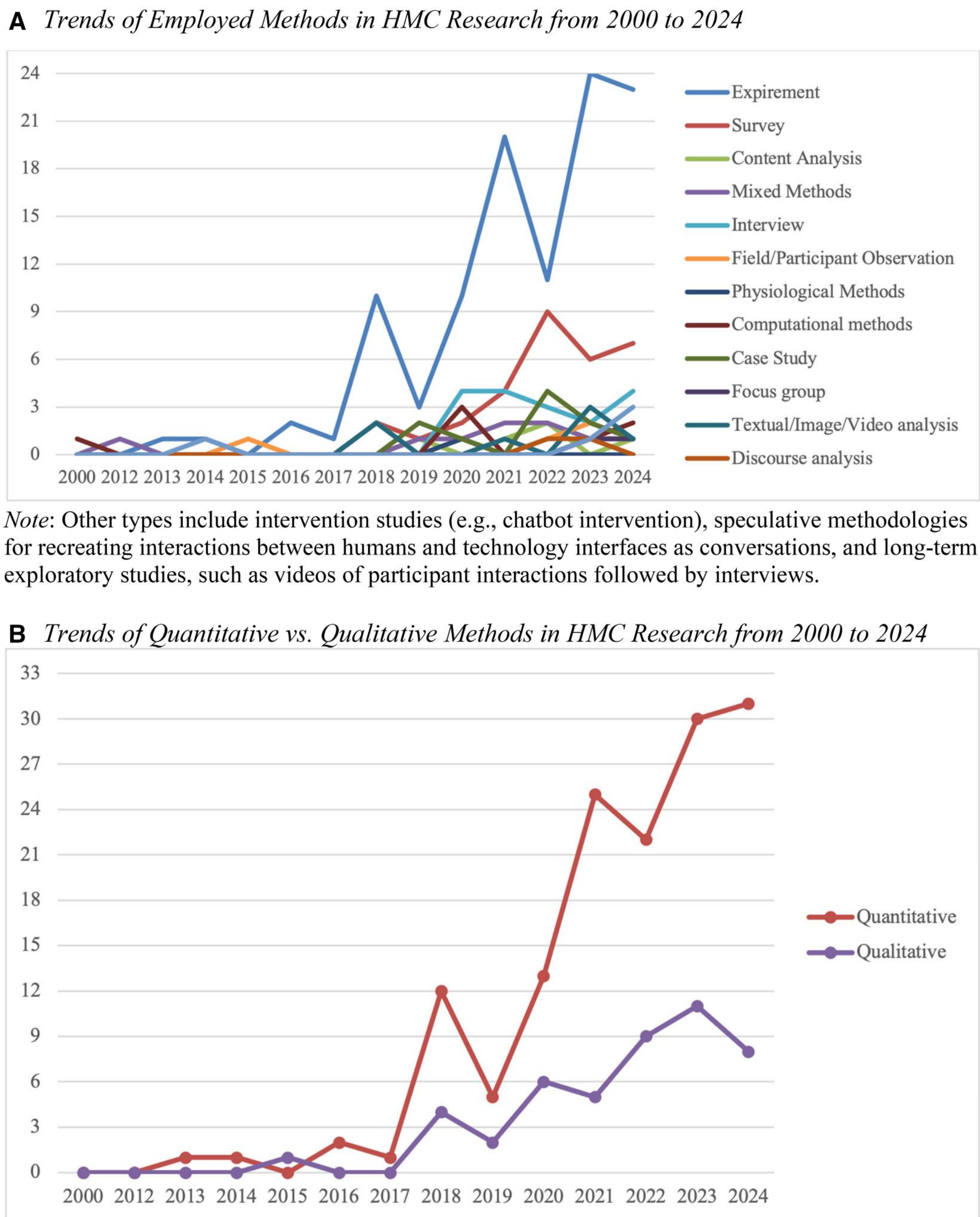

Figure 7 (A) Trends of employed methods in HMC research from 2000 to 2024. (B) Trends of quantitative vs. qualitative methods in HMC research from 2000 to 2024.

Note. Other types include intervention studies (e.g., chatbot intervention), speculative methodologies for recreating interactions between humans and technology interfaces as conversations, and long-term exploratory studies, such as videos of participant interactions followed by interviews.

and education" and "AI journalism and news automation" reflect the application of HMC perspectives to specialized areas such as education and automated news production.

To answer RQ5b, Figure 9 visualizes how topic prevalence has changed from 2000 to 2024. Within the limited number of studies in the earliest period (2000–2018), research centered primarily on "social and mind perceptions of social robots," indicating an initial emphasis on physically embodied agents and how people interpret their social cues. Around 2020, the field demonstrated a broadened scope to include more studies on "chatbots and social disclosure," "voice assistants and genders," and "social presence and relational development with virtual agents," reflecting the growing use of conversational and voice-based AI (e.g., Amazon Echo, Siri) in everyday communication. The most pronounced increases after 2022 appeared in "social media engagement with virtual humans" and "AI journalism and news automation," which aligns with the rapid rise of generative AI, virtual influencers, and automated news tools.

Figure 10 displays the proportional distribution of topics by year. The patterns show that HMC has shifted from being

Table 7 Summary of BERTopic-derived research themes.

Topic	Label	Brief description
1	AI teachers and education	Studies on AI/robot instructors, pedagogical interactions, and learners' perceptions of credibility and social presence.
2	AI journalism and news automation	Research on automated newswriting, newsroom chatbots, and audience trust in AI-generated journalism.
3	Voice assistants and genders	Research examining how gendered voices and social norms shape expectations and user trust in voice assistants.
4	Chatbots and social disclosure	Studies on how conversational and emotional disclosure cues influence user satisfaction, warmth, and authenticity.
5	Trust in machines' decision-making	Research addressing trust, responsibility attribution, and performance assessments in human–machine decision contexts.
6	Digital identity, privacy, and autonomy	Scholarship on how algorithmic systems reshape perceived identity, privacy practices, and autonomy.
7	Social and mind perceptions of social robots	Studies analyzing social perception, moral evaluation, and mind attribution toward robots in human–robot interaction.
8	Social presence and relational development with virtual agents	Work on how virtual agents (e.g., Siri, IVAs) foster relational closeness and social presence.
9	Social media engagement with virtual humans	Research examining how virtual humans use emotional expression on social media and how users respond affectively and behaviorally.

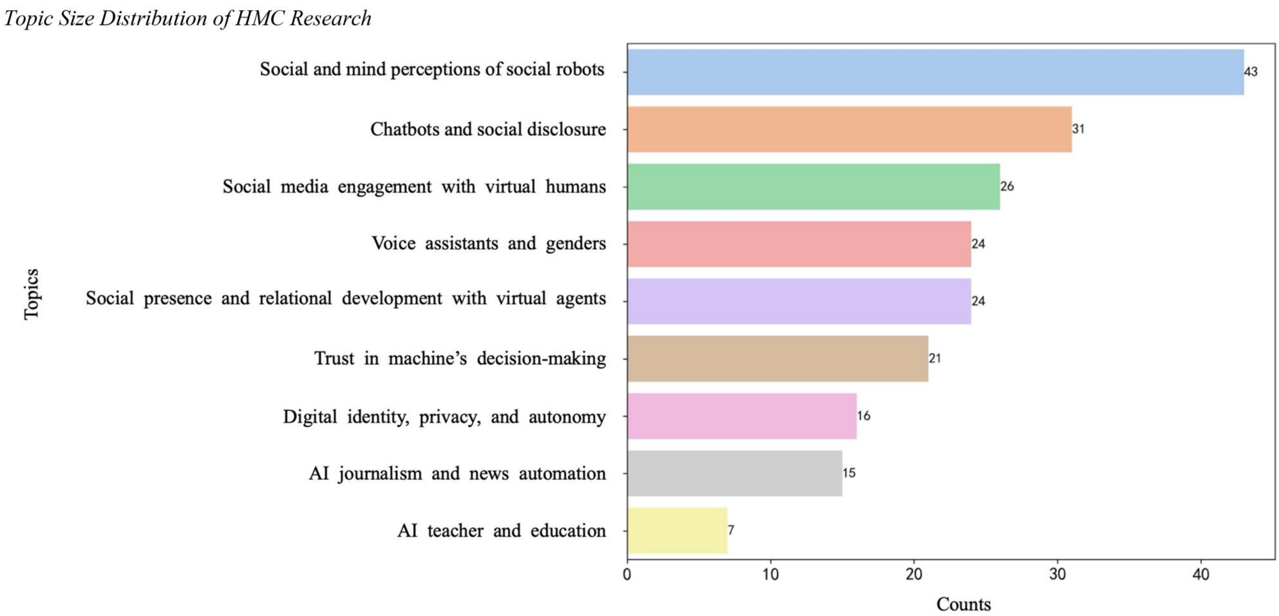

Figure 8 Topic size distribution of HMC research.

centered around one dominant topic to encompassing a wider range of interconnected research streams. Additional BERTopic outputs are provided in the Supplementary Appendix.

Discussion

This systematic review analyzed 209 empirical studies on HMC published between 2000 and 2024, with a focus on disciplinary affiliations, theoretical frameworks, methodological approaches, and the types of technologies examined. The reviewed sample is notably interdisciplinary, drawing from diverse theoretical perspectives and employing a range of empirical methods. In addition to mapping key research trends, this review aims to offer critical insights that support the continued development and consolidation of HMC.

Theoretical frameworks: prevailing psychological approaches

Based on our results, the CASA paradigm and the Media Equation appeared to be the most frequently used frameworks between 2000 and 2024. This pattern suggests that many scholars approached HMC through the lens of individuals' social responses to communicative technologies and used it as the

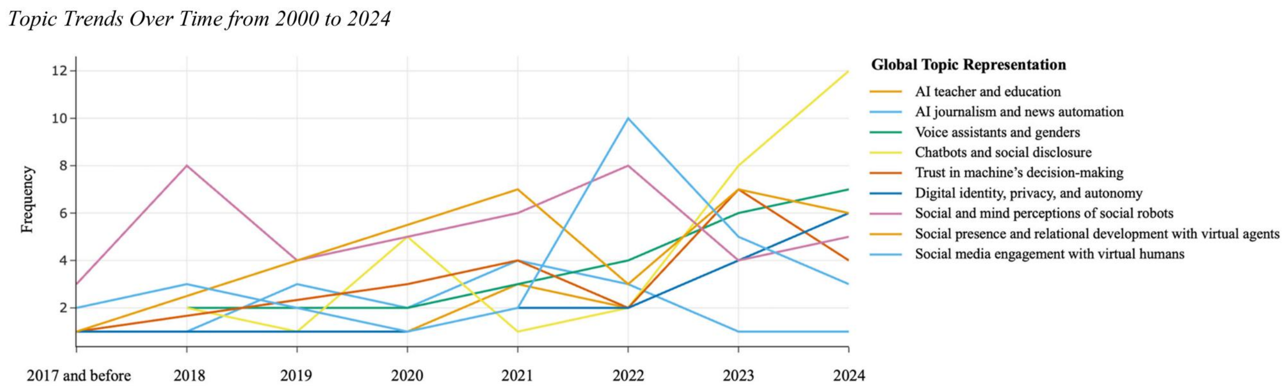

Figure 9 Topic trends over time from 2000 to 2024.

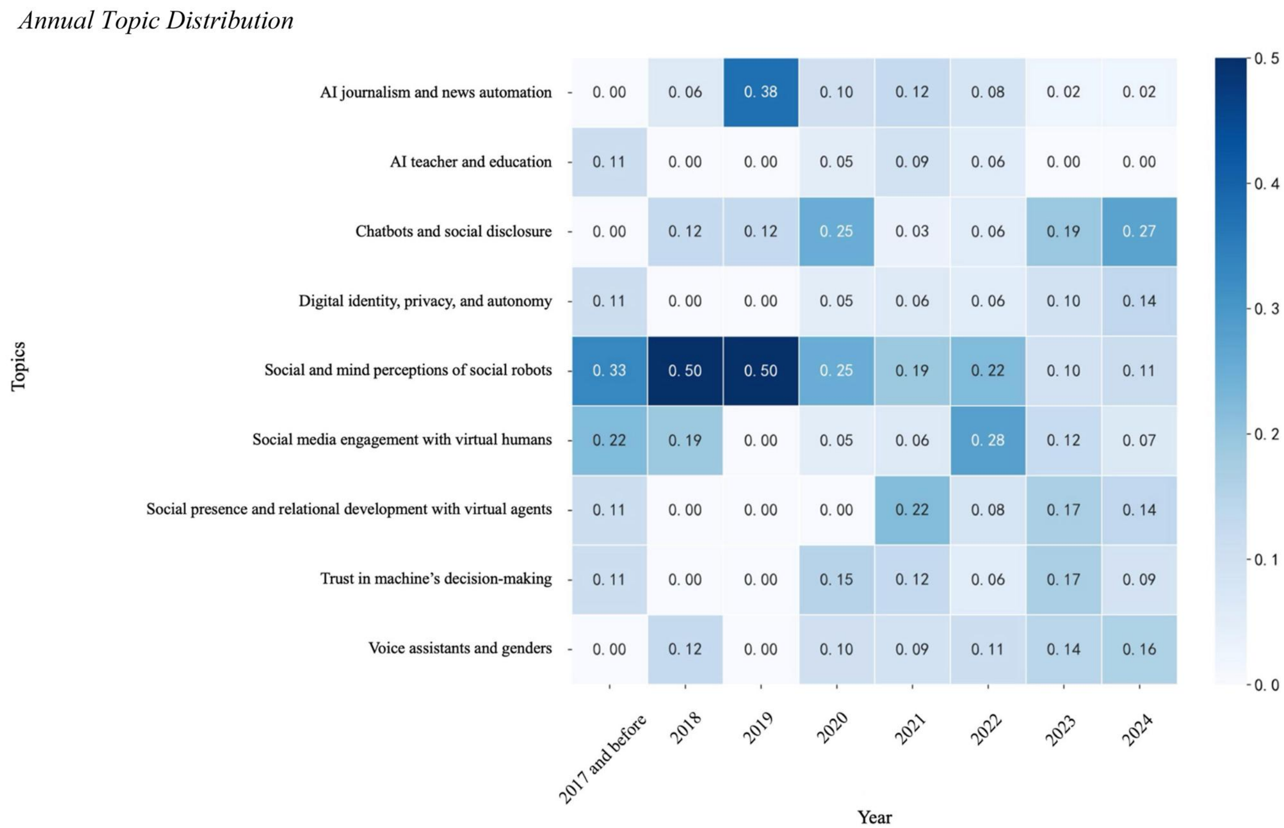

Figure 10 Annual topic distribution.

Note. Each cell represents the proportion of articles for a given topic within that year (row-normalized). Values closer to one indicate that the topic accounted for a large share of HMC publications in that year.

stepping-off point in their research (van der Goot & Etzrodt, 2023). This tendency not only reflects the wide application of these frameworks in explaining users' communication with emerging technologies but also highlights how scholars have invested efforts in reinvigorating these frameworks when growing research has been attending to the effects of various forms of AI technologies (e.g., Gambino et al., 2020; Lombard & Xu, 2021).

Theories of presence and the MAIN model followed as the second and third most commonly applied theoretical frameworks. Theories of presence capture scholars' growing interest in how individuals experience virtual or artificial social actors as real actors. In parallel, the MAIN model offers a heuristic-based perspective that links interface cues (e.g., bandwagon cues) to users' mental shortcuts (Sundar, 2008). The model focuses on technology affordances and delineates the boundary between mindless social responses and heuristically driven, belief-based evaluations (Lee, 2024).

Beyond these prevailing frameworks, other theories, such as the theory of mind, have been employed to explore how perceived cognitive capacity and human-likeness in technologies influence user responses (Banks, 2020). In addition, scholars have applied theoretical frameworks, such as TAM (e.g., Choung et al., 2024), actor-network theory (e.g., Ringel & Ribak, 2021), uncanny valley theory (e.g., Li et al., 2024), and attribution theory (e.g., Hong et al., 2021), in their works. Overall, the predominance of CASA, the Media Equation, presence, and the MAIN model suggests that HMC has largely concentrated on how users perceive and react to communicative technologies, especially through cues related to sociality, presence, and interface design. This orientation has been productive in establishing HMC as an empirical area of inquiry, but it also indicates that broader sociocultural, philosophical, and critical approaches remain comparatively underdeveloped. As a result, much of the field's theoretical growth has occurred through the extension of existing psychological and media-effects frameworks rather than through the development of more interpretive or structurally oriented explanations of human–machine relations.

Technologies: from physical embodiment to virtual agents and generative AI

Regarding the technologies investigated in HMC research, virtual agents and algorithmic or AI-generated content, including generative AI or LLMs in our coding scheme, have been dominant compared to other technologies. Simultaneously, investigations on smart devices and IoT technologies have also witnessed an increase. Two noteworthy contrasts emerged across time periods: from 2000 to 2018, physical robots (37.0%) were the most frequently studied technology. However, between 2019 and 2024, the focus shifted, with virtual agents becoming the most frequently examined technology (39.4%), followed by algorithms, AI-generated content, or generative AI (25.8%). By contrast, the amount of research on physical robots declined, indicating a decreasing emphasis on embodied machines and a rising interest in disembodied, text-based AI agents. This shift reflects a broader transition in HMC research: the rise of generative AI and LLMs marks a turning phase where these technologies are narrowing the boundaries between communication tools and communicative partners (Banks & de Graaf, 2020). LLMs now engage in the co-construction of contextually situated messages, serving both as tools that act on behalf of users and as interlocutors that engage with users, thereby functioning as automated social actors (Hancock et al., 2020; Hepp et al., 2023). Looking ahead, HMC scholarship may increasingly situate LLMs within the broader communicative AI lens to decode how platform-scale AI systems embed artificial sociality into the fabric of everyday discourse (Hepp et al., 2024).

Methodological imbalance and interdisciplinary dynamics

The analyses of research methods used in prior HMC research indicated an imbalance between quantitative ($n = 143$, 68.4%) and qualitative ($n = 46$, 22.0%) approaches. This pattern aligns with broader methodological trends in communication research (Khang et al., 2012; Kim et al., 2017; Peng et al., 2013) and is consistent with prior findings that most HMC studies rely on lab- or survey-based designs (Richards et al., 2022). Across the review period, experiments, surveys, and interviews were the most frequently used methods, followed by case studies, mixed methods, computational methods, and textual analysis. The prominence of experiments and surveys suggests that HMC scholars have primarily focused on measuring attitudinal and behavioral responses to emerging technologies. Methodological choices also varied by technology type: virtual agents were most often studied through experiments and surveys, whereas algorithms, AI-generated content, and LLMs were examined more often through surveys. This pattern may shift as LLMs become increasingly embedded in other technologies, including robots and virtual agents.

At the same time, the field's quantitative emphasis does not mean that qualitative work has been absent. Interviews, the most commonly used qualitative method in HMC research, increased from two studies between 2000 and 2018 (8.0%) to 17 studies between 2019 and 2024 (9.2%). These studies have been especially valuable for examining meaning-making processes surrounding algorithmic systems (Schwartz & Mahnke, 2021), automated journalism (Wu et al., 2019), and the evolving roles of LLMs as social and cultural artifacts (Liu et al., 2024).

Taken together, these patterns suggest that HMC scholarship has long been more focused on identifying perceptual responses to machines than on examining how communication with machines unfolds in everyday settings. Quantitative approaches remain essential, but qualitative and interpretive work is equally needed to illuminate how users make sense of these interactions over time and how broader cultural, social, and institutional contexts shape them (Hepp et al., 2023; Pan & Mou, 2024). Figurational-sociological, ethnographic, and other practice-oriented approaches may be especially useful for uncovering how people adopt, negotiate, and normalize communicative technologies in daily life (Hepp et al., 2024; van der Goot & Etzrodt, 2023). Echoing Fortunati and Edwards' (2021) perspective, this review advocates for more diversified methodological lenses, such as physiological measures, field observations, discourse analysis, and case studies, to capture the nuanced and evolving nature of HMC phenomena across various technological forms and communication contexts.

The analysis of the affiliations of HMC scholars further implied a high degree of interdisciplinarity in HMC scholarship. Our findings indicate that the most active disciplines contributing to HMC research are communication, computer science, and information science. Notably, since HMC became an official interest group at the ICA conference in 2019, there has been a significant increase in publications within the communication field. Yet, we also acknowledge that as HMC is rooted in communication research and the systematic review includes mostly communication-related journals, it is not surprising to see that the highest affiliations are within communication institutions. What merits note is that scholars from information science, computer science, and business have contributed an expanding share to HMC studies. Together, these findings indicate that HMC research is driven not only by the need to illuminate the psychological aspects of the communication process (Lewis et al., 2019) but also by the design and user experience research pursued by the interests of the engineering and information technology fields (Guzman, 2018). Additionally, the geographic diversity of the research points to the international scope of the field, with studies conducted in countries such as the United States, Germany, and China, as well as in cross-national contexts.

Evolution of research themes in HMC

The BERTopic analysis offers additional insight into how the intellectual conversations within HMC has evolved over the past 25 years. Early studies were heavily concentrated on mind perception and social responses to social robots, which is consistent with the finding that CASA and the Media Equation remained the most frequently applied frameworks in past HMC studies. However, the thematic landscape diversified substantially after 2020. Topics such as chatbots and social disclosure, voice assistants and gender, and relational development with virtual agents have emerged as core areas of inquiry. The diversification occurs probably because researchers began to have easy and long-term access to AI-based technologies, including virtual agents and voice assistants (e.g., Alexa, Replika). This pattern is consistent with the trends observed in the manual coding, where virtual agents, algorithmic systems, and AI-generated content show a steady increase over time. Following the public release of LLMs, the thematic landscape expanded further, suggesting that research on LLMs will likely shape the next phase of HMC scholarship. Overall, these patterns indicate that HMC scholarship is increasingly grappling with AI systems that operate both as communicative partners and as algorithmic infrastructures shaping public discourse at scale. This thematic diversification suggests that HMC is maturing into a broader and more interconnected field that engages a wider set of communicative, cultural, and socio-technical questions.

Boundaries: technology transformation, theoretical integration, and methodological innovation

The findings of the systematic review can further inform how the boundaries of HMC may continue to evolve. First, the range of technologies considered within HMC is likely to expand. While early studies concentrated on physically embodied machines such as robots and self-piloting vehicles, our review shows a growing focus on embodied and disembodied virtual agents, as well as algorithms, generative AI, and LLMs. Especially given that LLMs are increasingly taking multiple roles, including but not limited to search engines, grammar checkers, companions, assistants, and multimedia creators, and that they are connected to multiple mobile and robotic platforms, we may see a vast discussion about how users navigate between their roles as mediators and as social companions. Similarly, the development of telepresence robots serves as another example of how technologies may incorporate both HMC and mediated communication (Xu & Liao, 2020). Users' responses to the movements and the appearances of telepresence robots, along with their reactions to the remote human users in the screens of telepresence robots, have bridged both HMC and mediated communication, creating opportunities for future scholars to revisit the scope of HMC and bring in diverse scholarship to expand HMC. Within these increasingly blurred spaces, researchers might need to invest more efforts in identifying the key features of machines that define them as subjective communicators. Researchers could first propose a list of technology features (e.g., interactivity, language capacities, transparency) and then use a variable-based approach (Nass & Mason, 1990) to understand how these features position machines as interlocutors. Like how Sun et al. (2024) found that technological, symbolic, materialist, cultural, social, and cognitive dimensions might redefine the concept of emerging media, the future conceptualization and theorization of machines may also benefit from the investigation into multiple key constructs underlying machines.

Second, more theoretical frameworks from other fields will be involved in HMC research. As more disciplines are participating in the discussion about varied HMC phenomena, theories from not only communication but also other fields (e.g., STS, information science, political science) may make important contributions to HMC research. This research trend may occur as technologies become increasingly ubiquitous, multinatured, and context-aware, thus necessitating scholars' construction and development of both old and new frameworks to be used in HMC research. Suchman and Thimm (2024) suggested that more non-Western perspectives should be applied to understand societal relations with machines. Indeed, the evolving boundaries of HMC are bidirectional: while HMC theories can inform applied research in domains such as journalism, advertising, and business, studies rooted in these fields also generate insights that contribute back to the theoretical development of HMC (Guzman et al., 2023). One recent example is the conversation between explainable AI (XAI) and HMC (Xu & Shi, 2024), which advanced a two-level HMC framework that theorizes how individuals receive, perceive, and evaluate the explanations of AI's working mechanisms. This framework underscores the necessity to consider human engagement in AI's data labeling, model training, and outcome verification and demonstrates HMC scholars' potential in contributing to XAI by investigating the explanation sources, features, receivers, and effects.

Another area that may blur the boundaries of HMC is AI-mediated communication (Hancock et al., 2020). In this sense, LLMs should not be understood as a single type of communicative entity; rather, their role depends on the interactional context in which they are embedded. As users rely on LLMs to revise emails, prepare for interviews, and create online profiles, interactions with generative AI agents for interpersonal relationship maintenance or impression management will receive growing attention. On the one hand, LLMs serve as tools that users rely on to communicate with other human partners. On the other hand, sending prompts and receiving recommendations from LLMs is a classic HMC process. Here, AI-MC and HMC may converge and create new spaces for researchers to cooperate and advance theoretical contributions. Following this perspective, it might not be hard to imagine that the boundaries could be even more ambiguous, as users begin to rely on various LLMs to interact with machines, including with LLMs per se. A recent study suggests that generative AI favors communications generated by LLMs per se (Laurito et al., 2025), which implies that future HMC work may further involve human communication with generative AI mediated by generative AI (e.g., users' reliance on GPT to create proper prompts to further communicate with Claude).

Third, the methodological approaches to HMC may become more heterogeneous in the future. Although quantitative research methods have been most often used in the past decade, given the strengths of triangulation and multiplism (Cook, 1985), a complete understanding of HMC is only possible when multiple methods are used to validate results, produce new knowledge, and further define the scope of the field. Furthermore, as LLMs begin to take more computational tasks, simulate human responses (Argyle et al., 2023; Peng & Yang, 2025; Yeykelis et al., 2024), create experimental stimuli, and reveal more accurate data analysis results, it is likely that future methods may increasingly incorporate LLMs as part of their methodological approaches. Again, LLMs may enrich researchers' adoption of methods and serve as new tools to help explore human–machine relationships.

Conclusions and future directions

Based on an analysis of 209 HMC articles published between 2000 and 2024, this systematic review charts the intellectual trajectory of HMC as an evolving research domain. By examining theoretical frameworks, methodological practices, disciplinary affiliations, technological foci, and thematic trajectories, this review offers the most comprehensive account to date of how HMC has emerged and transformed across 25 years of scholarship. The findings about the application of the theoretical frameworks in HMC encourage scholars to focus more on theories related to the social, political, philosophical, and cultural implications of HMC. The existing imbalance between the use of quantitative and qualitative methods encourages future scholars to develop deeper understandings of HMC from a more interpretive and meaning-making angle. The growth of interdisciplinarity and the diversity of technologies have also highlighted the importance of examining HMC from diverse theoretical perspectives. Overall, our comprehensive review of 25 years of published articles outlines the academic trajectory of the development of the HMC community and highlights the key areas needed for future research for the field's progression. It also serves as both a checkpoint and starting point for scholars outside HMC spaces to have a grounded understanding of the current state of the field while opening pathways for engaging in ongoing conversations within the field.

While this study presents the status quo of the HMC field over the past 25 years, future work could benefit from a more inclusive approach to analyzing HMC publications. First, in addition to journal articles, future systematic reviews should also consider peer-reviewed proceedings, such as those from ACM and SIGCHI. Book chapters, monographs, or edited collections related to philosophical discussions about machines, STS, legal and ethical challenges, and cultural studies should also be included. Additionally, non-English texts could be included to more precisely represent the scope of HMC research.

Second, this study coded only the affiliations of the first authors. Given that engineering and computer science fields often place more weight on the last and corresponding authors, a more comprehensive analysis could include coding all listed authors.

Third, while this review focused on studies that explicitly position themselves as HMC research, future reviews might adopt a broader, layered strategy by using additional terms (e.g., human–AI communication, communicative AI, chatbot, AI companion, conversational agent, or digital interlocutor) to explore the wider intellectual ecosystem surrounding HMC. Such an ontology-driven approach would be especially useful for mapping research on technologies as communicative subjects beyond self-identified HMC scholarship, although it would also require greater interpretive judgment in determining what should be included within the field's boundaries.

Fourth, as the integration of LLMs becomes more widespread across various systems, creating mutually exclusive categories to differentiate technologies is increasingly challenging. Our coding, therefore, reflects a case-by-case evaluation of how each study conceptualizes the communicative role of technology, rather than adhering to a fixed ontological taxonomy. As technologies become more multimodal, adaptive, and integrated across platforms, future reviews may need to adopt multilayered classification frameworks to better capture the fluid boundaries among agents, interfaces, and algorithmic systems.

Finally, this review highlights a fundamental theoretical question that our field has only begun to address: what capacities must a technology possess to be treated as a communicator rather than merely a channel? As generative AI and large language models become increasingly integrated into social robots, virtual agents, smart devices, and algorithmic systems, these communicative abilities blur the line between tools and conversation partners. A crucial next step for HMC scholarship is to establish more precise conceptual and empirical criteria for identifying when, and under what conditions, machines are considered communicative subjects.

Supplementary material

This manuscript features online supplementary material including the items of the study, the dataset, study materials, and additional analyses: https://linkprotect.cudasvc.com/url?a=https%3a%2f%2fosf.io%2f4wn7s%2foverview%3fview_only%3dbac766ee63594f3fbeb45e366dd53b41&c=E,1,3RVIHo0bPr3PQlE6JiRkIKPK8-U2CCr9YKpToLW7kAbFIe7whOlpkVbL_8hZCkJb42n1hwo8Z7Z7-lz-oMkxjpTHFbZnQMgqR0CVNlc8dYAmTzHDX2w51_M,&typo=1

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