Bridging Minds and Machines: Mapping the Terrain of Communication in Human-AI Teams — A Systematic Literature Review

WEN DUAN, Clemson University, USA
RUI ZHANG, University of Colorado Boulder, USA
NAN WENG, Clemson University, USA
GUO FREEMAN, Clemson University, USA
NATHAN MCNEESE, Clemson University, USA

As AI becomes increasingly adept at communicating with humans in natural language and complementing human skills in various collaborative and teamwork settings, how the CSCW community understands the evolving role of communication in human-AI teams (HATs) urgently needs to keep pace with these technological advancements. To provide a structured overview of the scientific knowledge regarding communication in HATs, we conducted a systematic review of 74 articles, synthesizing how communication has been conceptualized, operationalized, and linked to team processes and outcomes. Our review reveals that existing research overwhelmingly relies on text-based communication and is concentrated in controlled experimental and simulated settings, with communication outcomes often measured using platform-specific or frequency-based metrics, limiting generalizability across tasks and contexts. Across this literature, communication is most commonly modeled through a functional input-output lens, leaving the communicative processes that transform inputs into taskwork and teamwork outcomes under-explored. We synthesize these findings into an input–process–output framework that reconceptualizes communication as a socially embedded team process, which can inform methodological choices and the purposeful and responsible design of communicative AI teammates in CSCW contexts.

CCS Concepts: • **General and reference → Surveys and overviews**; • **Human-centered computing → HCI theory, concepts and models**.

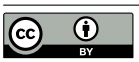
Additional Key Words and Phrases: Human-AI Teaming, Human-Agent Teaming, Human-AI Collaboration, Human-AI Communication, Human-Autonomy Teaming

ACM Reference Format:
Wen Duan, Rui Zhang, Nan Weng, Guo Freeman, and Nathan McNeese. 2026. Bridging Minds and Machines: Mapping the Terrain of Communication in Human-AI Teams — A Systematic Literature Review. *Proc. ACM Hum.-Comput. Interact.* 10, 6, Article CSCW058 (October 2026), 33 pages. https://doi.org/10.1145/3816906

1 Introduction

Rapid advancements in Artificial Intelligence (AI) have made human-AI teaming (HAT) both a socio-technical reality and an explosive field of research in the HCI and CSCW communities [90, 157, 196]. Indeed, as of May 2024, the search term ”human-AI team” in Google Scholar yielded a total of 981 records, and 914 of them were published since 2020. In this paper, we adopt the well-established

Authors' Contact Information: Wen Duan, Clemson University, Clemson, SC, USA, wend@clemson.edu; Rui Zhang, University of Colorado Boulder, Boulder, CO, USA, rui.z3@hotmail.com; Nan Weng, Clemson University, Clemson, SC, USA, nweng@clemson.edu; Guo Freeman, Clemson University, Clemson, SC, USA, guof@clemson.edu; Nathan McNeese, Clemson University, Clemson, SC, USA, mcneese@clemson.edu.



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ACM 2573-0142/2026/10-ARTCSCW058
https://doi.org/10.1145/3816906

definition of Human-AI Teaming (HAT) as "interdependence in activity and outcomes involving one or more humans and one or more autonomous agents, wherein each human and autonomous agent is recognized as a unique team member occupying a distinct role on the team, and in which the members strive to achieve a common goal as a collective" ([144], p.8). As such, HATs are defined not by the number of humans involved but by the presence of **teamwork** that requires shared goals, interdependence, and joint activity. This definition thus positions AI agents as genuine teammates [55, 199] rather than technical tools, which can actively participate in team processes and coordinate with humans to complete team tasks and share team-level responsibilities.

It is primarily through communication that these team processes and task coordination take place. However, despite the exponential growth in HAT research, our understanding of the effective means of communication for HATs is highly limited due to scattered and inconsistent findings. For instance, while some HAT research has suggested a positive association between the amount of team communication and team situation awareness [132], performance [48], and team shared mental model [157], others (such as [37]) have found a negative correlation between the number of messages and team performance. Additionally, greater information shared in human-AI communication (i.e., greater transparency [163, 190] or explanability [117]) does not always lead to better decisions or trust [154]. Furthermore, there is a lack of consistency in how communication behaviors are categorized, with terms like "communication style" [179, 189] and "communication directionality" [3, 44, 191] being conceptualized and operationalized differently across studies.

These inconsistencies point to a foundational challenge in HAT research: despite broad agreement that communication is central to effective human–AI teaming, there is little shared understanding of how communication is conceptualized, operationalized, and examined across studies. This fragmentation limits the ability of CSCW and related fields to compare findings, accumulate knowledge, and translate empirical results into principled design guidance, especially as AI systems increasingly act as communicative teammates rather than passive tools [199]. Addressing this gap is a necessary precursor to advancing theories of communication and teamwork in HATs. Therefore, this systematic review focuses on clarifying how communication has been studied in previous HAT research, and seeks to answer the following research questions:

- **RQ1:** How and what do humans and AI agents communicate in HATs?
  - **RQ1a:** How is human-AI communication operationalized as independent variables in HAT research?
  - **RQ1b:** How does human-AI communication impact other team processes and outcomes?
- **RQ2:** How might the research setup (e.g., characteristics of AI or team) impact human-AI communication in HATs?
  - **RQ2a:** How is human-AI communication measured as outcome variables in HAT research?
  - **RQ2b:** What factors have been examined to impact human-AI communication in HATs?

The structure of our results reflects two distinct perspectives on communication in HATs. The first set of research questions (RQ1, RQ1a, RQ1b) treats communication as an **input**, synthesizing how it is conceptualized, operationalized, and examined in relation to team processes and outcomes (presented in Section 4). The second set (RQ2, RQ2a, RQ2b) treats communication as an **outcome**, focusing on how features of the research setup influence communication and how communication is measured in experimental studies (presented in Section 5). While the two overarching questions (RQ1, RQ2) synthesize trends across all reviewed studies regardless of method, the sub-questions (RQ1a, RQ1b, RQ2a, RQ2b) focus specifically on how communication has been studied in **experimental research**, enabling a more targeted analysis of causal claims and measurement strategies.

This systematic review makes several contributions to HCI and CSCW research on human-AI teaming. First, it consolidates the existing scientific knowledge of the communication modality, directionality, behavior, and content, as well as their influencing factors and impacts, as examined in HAT research. As such, this work serves as a foundational milestone that synthesizes a currently disorganized domain, providing CSCW and HCI researchers and practitioners with a comprehensive overview of communication in HATs to guide future research and applications. Second, this review identifies significant gaps in the current literature, offering a roadmap and methodological directions for addressing the gaps. Third, drawing on the findings from this review and theories of human team and human-computer interaction, we propose a theoretical framework specifically for conceptualizing and researching the communication in HATs, suggesting it be viewed across the input, process, and output stages. This framework will effectively guide future research efforts in CSCW to advance our understanding of communication in HATs in a systematic manner. Lastly, this review yields implications for purposefully designing effective communication for future HATs to achieve desired outcomes.

2 Background

2.1 Human-AI Teaming

Human-AI teaming (HAT) is defined as "interdependence in activity and outcomes involving one or more humans and one or more autonomous agents, wherein each human and autonomous agent is recognized as a unique team member occupying a distinct role on the team, and in which the members strive to achieve a common goal as a collective" ([144], p.8). By dividing workloads in the collaborative teaming environment, humans and AI agents could also work toward a collective goal and enhance their task performance by reducing work duplication and redundancy [2, 67]. With the rapid development of machine learning, recent AI agents have successfully demonstrated advanced computational abilities and are also capable of behaving ethically, intuitively, and empathetically [1, 95]. In particular, autonomous AI agents are not vulnerable to emotional and psychological influences, and they become more adaptive to complex tasks and dynamic interactive team environments, which enhance team efficiency, performance, and effectiveness [1, 63]. Thus, the AI agent is considered a legitimate teammate and human partner rather than a tool as it has greater potential to behave in a more ethical and effective way in human-AI teams [162].

The implementation of HATs has faced unexpected challenges. One major issue is the perception of AI as an "at risk" partner requiring human protection [135, 143], sparking ongoing debates about whether autonomous agents should be viewed as true teammates [147]. Communication also remains a critical challenge. As an essential approach to receiving and sharing information in collaborative and cooperative human-AI teams, the communication strategy depends on the specific team tasks and team environments [199]. However, due to the dynamic team environment and complex tasks, current AI teammates lack proactive communication and appropriate communication channels in HATs, which decreases human trust and situational awareness [196]. In the next section, we review prior work on communication in human-AI teams to provide deeper insights.

2.2 Communication in Human-AI Teams

Communication is vital for team coordination and collaboration by facilitating task-related information sharing [55]. Unlike human-only teams, communication in HATs poses unique challenges due to AI's machine nature [196]. Given the context-dependent feature of communication and teamwork, most of existing research on communication in HATs has focused on quantifiable communication attributes, such as *communication quantity and frequency* [44, 48, 144]. Previous work

on communication in HATs has indicated that team communication quantity is related to team situation awareness and team performance [37]. Another study has shown a positive relationship between AI's communication and shared mental models [84].

Among HAT research that employs a certain level of communication, a majority has applied text-based communication for humans and AI teammates to share essential information and coordinate [43, 132, 174]. For instance, previous work has explored the impact of AI's ethics on human trust using a military simulation game, where text-based communication was employed for two humans and one AI teammate to coordinate and proceed team tasks [159, 174]. Another study investigated trust between humans and AI in a 2D game environment where the human teammate used buttons to send pre-developed messages to the AI teammate [105]. The rapid advancement of natural language processing models within the past several years is pushing AI agents towards having smooth communication with humans without using pre-developed messages. However, communication in human-AI teams has requirements that are beyond smooth communication in human-AI interaction. For instance, human-AI team tasks requires AI teammates to communicate certain task-related information to human teammates at the appropriate time. In order to perform such behaviors, the AI teammate needs to (a) have an understanding of team member roles and team tasks, (b) synthesize various types of information to coordinate effectively, including received human teammate's communication and dynamic task process, and (c) provide necessary information to humans when needed. The capability of communicating dynamic task-related information in a timely manner is essential for achieving outstanding team performance [199]. Thus, it is important to review current research on communication in human-AI teams and gain an in-depth understanding of how communication is designed in HATs to develop human trust, facilitate team processes, and contribute to team performance.

Prior review work has acknowledged the importance of communication in HAT but has not examined it in-depth as the primary analytic focus. Notably, O'Neill et al. [144]'s comprehensive review of human–autonomy teaming identifies communication as the only variable discussed as a potential mediator between team inputs and outcomes. However, this observation is based on only four studies that explicitly examined communication, limiting the strength and specificity of the conclusions that can be drawn. Similarly, Berretta et al. [11]'s human-centered scoping review and network analysis further demonstrate that communication is conceptually central to how HAT is defined, but treats it as an embedded element within broader conceptual clusters rather than as an object of empirical synthesis. Endsley [64]'s framework emphasizes communication as the mechanism through which shared situation awareness is achieved, largely operationalized through transparency, explainability, and shared displays, but focuses on information transfer rather than interactional processes. A recent systematic review of trust in HATs [52] documents that communication-related factors such as communication style, apology, or uncertainty communication are rarely examined, and when they are, they are treated as manipulations of trust rather than as the core analytic focus. Together, these reviews suggest that communication is central to teamwork outcomes, but leave it methodologically fragmented and theoretically underdeveloped. None of them systematically synthesizes how communication is defined, operationalized, or measured across studies. As a result, it becomes difficult to explain why similar HAT systems yield divergent teamwork outcomes across contexts, thus providing limited guidance for CSCW researchers and designers seeking to build AI teammates that participate meaningfully in cooperative work.

3 Method

We conducted the systematic review following the guidelines provided in the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA; [145]), which starts with a systematic

literature search to identify relevant publications, followed by the application of a well-defined set of inclusion and exclusion criteria to screen for eligibility.

3.1 Literature Search Strategies and Sampling

Our primary search terms included various combinations of communication (or collaboration, coordination), team, and human-AI (or human-autonomy, human-agent). A full list of search strings and strategies is detailed in Table 1.

Database	Search string	Filters	Results
ACM Digital Library	[[All: communicat*] OR [All: coordinat*] OR [All: collaborat*]] AND [All: team*] AND [[All: "human-ai"] OR [All: "human-agent"] OR [All: "human-autonomy"]]	Content type: research article + extended abstract + short paper	1820
IEEE Xplore	("Full Text Only":communicat* OR "Full Text Only":coordinat* OR "Full Text Only":collaborat*) AND ("Full Text Only":team*) AND ("Full Text Only":"human-AI" OR "Full Text Only":"human-agent" OR "Full Text Only":"human-autonomy")	Conferences + Journals + Early Access Articles, excluding Magazines and Books	1655
Web of Science	TS=(communicat* AND team* AND "human-AI") OR TS=(coordinat* AND team* AND "human-AI") OR TS=(collaborat* AND team* AND "human-AI") OR TS=(communicat* AND team* AND "human-agent") OR TS=(coordinat* AND team* AND "human-agent") OR TS=(collaborat* AND team* AND "human-agent") OR TS=(communicat* AND team* AND "human-autonomy") OR TS=(coordinat* AND team* AND "human-autonomy") OR TS=(collaborat* AND team* AND "human-autonomy")	Proceeding paper + Article, excluding Book Chapters, Review Article, and Data Paper	201

Table 1. **Literature Search Strategies and Results.** a. Asterisk (*) denotes wildcards that include any number of unknown characters. b. TS in Web of Science searches title, abstract, Keyword Plus, and author keywords.

The literature search occurred in three library databases that are most used for CSCW and related research on HATs: ACM digital library, IEEE Xplore, and Web of Science. We set the scope of the literature search to include all relevant studies published up to May 31, 2024. We used the filtering tools available in the three databases to refine our search scope by limiting the search to only include journal articles, proceedings, extended abstracts, excluding review articles, books, tutorials, etc. This step allowed us to conduct an initial screening of the non-empirical, non-peer-reviewed, or non-archival articles, to facilitate manual screening. To ensure comprehensiveness, the original pool also included the entire corpus of [144]'s high-level review on human-autonomy teams (see Figure 1). The search yielded 3752 records that were entered into a citation management tool Zotero to automatically identify duplicates. After removing duplicates and editorial materials, 1921 records remained for retrieval. A total of 1905 English publications were successfully retrieved for assessment based on the following inclusion and exclusion criteria:

- **IC1:** It must be empirical research.
- **IC2:** It must involve at least one autonomous AI agent and one human participant.
- **IC3:** The autonomous AI agent must be, or be perceived by participants to be capable of performing tasks independent of human control.
- **IC4:** The autonomous AI agent(s) and the human(s) must communicate to achieve a shared goal as a team.
- **IC5:** The research must identify and frame itself as human-AI (or human-agent, human-autonomy) teaming research.
- **EC1:** *Non-empirical work*: such as conceptual models and theoretical frameworks, reviews and surveys of literature, view pieces, discussion of ethical issues, etc.

- **EC2:** *Off-topic*: such as research on AI and automation technology adoption and use for various teams
- **EC3:** *Keywords light mention, not focus*: The search terms are only mentioned in the abstract, related work, or discussion as a motivation or a recommendation for future work, but the work itself does not investigate communication in HATs. Or keywords lightly mentioned in the participants' quotes, method description, etc. (e.g., "the research team", "team lead").
- **EC4:** *Missing search term*: A subset of the search terms connected by the AND operator are not present in the specified search areas, which should not have been listed as results found by the search engine.
- **EC5:** *Physical forms of autonomous agents*: HATs involving physical robots, drones, or telepresence robots should be excluded.

ICs 2-5 are used to determine that the article positions itself as, or can be deemed HAT research following O'Neill and colleagues' [144] definition of Human-Autonomy Teams, where there is at least one human and at least one autonomous agent, working interdependently to achieve a common goal. As such, studies that had participants control the agents, such as management of robots [24, 26] and unmanned vehicle control [40] were excluded. For IC4, we define communication as "the process of exchanging information, ideas, thoughts, feelings, or messages between human and AI teammates, which can occur through verbal, nonverbal, or visual means". Studies in which human(s) and agent(s) were not able or allowed to communicate in any way were excluded. Importantly, these criteria operationalize teamwork through communicative coordination toward a shared goal, rather than the number of human participants involved. As a result, dyadic configurations are included only when studies explicitly frame the human and AI as a team and examine communication in support of collective task outcomes, rather than individual user benefit[1]. For EC5, we intentionally excluded physical forms of agents to maintain analytic coherence in synthesizing communication processes. Prior work has shown that physical embodiment fundamentally alters the communication affordances available to autonomous agents [28, 101, 146, 156] and the social responses they elicit from humans [51, 114]. As a result, HATs involving physical robots, drones, or telepresence robots are excluded, allowing this review to focus on communication in non-physically embodied, interface-mediated human–AI teamwork. This scope is complementary to existing CSCW and HRI research on human-robot collaboration [161]. Determination of inclusion and subsequent coding of the data in the articles were completed by all of the authors.

As shown in Figure 1, during abstract/title screening, we were primarily concerned with excluding records that are non-empirical (IC1, EC1), do not involve human participants (e.g., pure computational) (IC2), off-topic (EC2), study physical forms of agents (EC5), or do not position itself as HAT research (IC5). Through full-text reviewing, we further verified the above-mentioned criteria by conducting a more detailed examination. This closer analysis enabled us to identify articles where the AI is not fully autonomous (IC3), does not engage in communication with human participants to achieve team goals (IC4), or where keywords are either mentioned only superficially (EC3) or entirely absent (EC4). A total of 74 papers were included in the final corpus.

3.2 Data Extraction and Coding

Once the final corpus of reviewed articles (N=74) was determined, three of the authors extracted information on the research method(s); the characteristics of the AI teammate(s), including the

[1]Systems such as MS Copilot or supervised autonomous driving may constitute HAT when they are studied as collaborative systems where human and AI coordinate actions and responsibilities through communication to achieve a shared goal. Conversely, when such systems primarily provide unilateral assistance without being framed as teamwork, they fall outside the scope of this review.

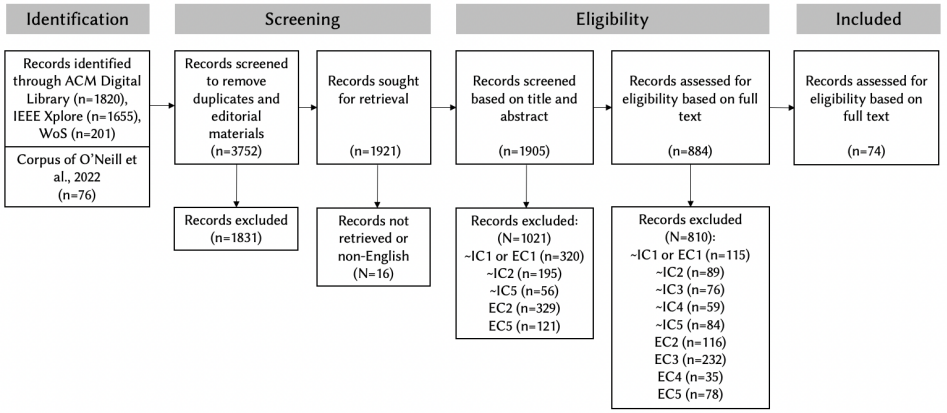

Fig. 1. **Literature Search Procedure.** Under Identification, Screening, Eligibility, and Included, the first row of boxes denote the total records (n) identified, screened and assessed during the main search through 3 databases. The second row of boxes denotes the number (n) of records excluded based on a specific inclusion criterion (IC) or exclusion criterion (EC). (e.g., "EC1 (n=x)" means x articles were excluded based on EC1; "~IC1 (n=y)" means y articles were excluded for NOT meeting IC1.)

ways in which human-AI interaction were realized (or AI control method), its visual appearance or embodiment, its role in relation to human teammates; the characteristics of the team, including the size and composition; the characteristics of the task and context; the communication modality (i.e., the channel through which communication occurs, such as text, audio, and visual), directionality (i.e., whether communication flows from human to AI, AI to human, or bidirectionally), and behavior or content. For studies that employed an experimental method, we also extracted information on whether communication was examined as independent or dependent variable(s), how communication was operationalized and/or measured, the factors that were examined to impact communication, and the dependent variables that communication was examined to impact.

We coded the extracted information in an inductive manner. In our collaborative spreadsheet, we first described the information in great detail, then performed an iterative categorization process similar to thematic analysis [17, 78]. During this process, we assigned initial codes, grouped the initial codes into high-level codes and themes, broke down, and refined the initial codes. Throughout the iterative process, three authors met periodically to discuss and resolve any disagreements.

3.3 The Corpus

We outline the temporal, disciplinary, geographical, and methodological characteristics of the resulting corpus of 74 articles. As shown in Figures 2 and 3, a great majority of the reviewed research (57/74, 77%) was conducted in the United States. The increase in the number of papers over the years suggests a growing interest in research on communication in HATs across fields of HCI (including venues such as CHI, CSCW, GROUP, Computers in Human Behavior, etc.), Human Factors and Ergonomics, HRI (e.g., International Journal of Social Robotics), social science (e.g., Frontiers in Communication), Engineering, and other interdisciplinary fields..

As seen in Figure 4, a great majority (84%) of the reviewed research employed only experimental method. Additionally, most of what reported mixed-method results used experiment as the primary method and post-experiment interview as the secondary method (6/74). Four studies conducted post-experiment interviews and reported only qualitative results. Of the two articles that did not

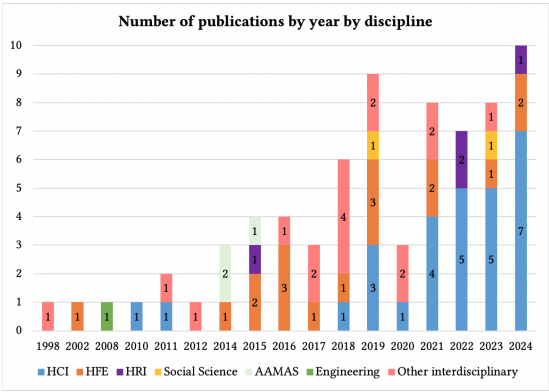

Fig. 2. The Number of Articles Studying or Involving Communication in HATs Included in This Review by Year by Discipline

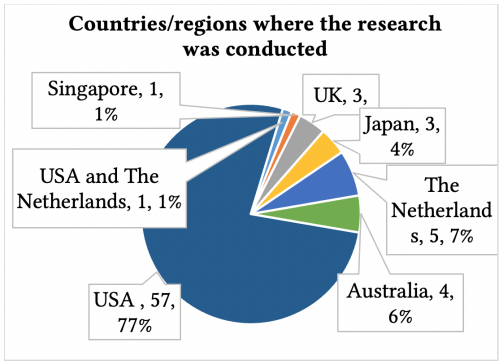

Fig. 3. Countries/regions in which the Reviewed Studies Took Place.

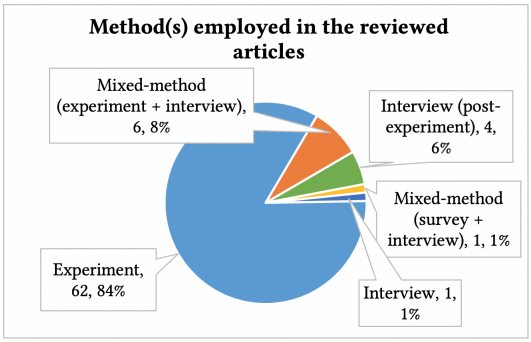

Fig. 4. Method(s) Employed in the Reviewed Studies

involve experimental data, one was based solely on interviews, while the other combined surveys with interviews.

4 The Conceptualization and Operationalization of Communication in HATs

This section examines how communication is conceptualized and empirically studied in HAT research. We begin by synthesizing patterns in modality, directionality, and the content and behavior of AI communication across all reviewed studies, regardless of methodological approach. Next, we turn to experimental studies that manipulate communication as an independent variable to assess its effects on team dynamics and outcomes.

Before proceeding, we first present our categorization of the reviewed papers into those that examined communication as an independent or dependent variable(s). As shown in Figure 5, thirty-two (43%) of the reviewed papers treated communication as an independent variable. Sixteen (23%) measured communication as a dependent variable. Fourteen (21%) used communication as both an independent and dependent variable. These categories do not apply for 12 papers in which communication was only involved in the human-AI teaming and collaboration process, rather than being examined as either an independent or dependent variable.

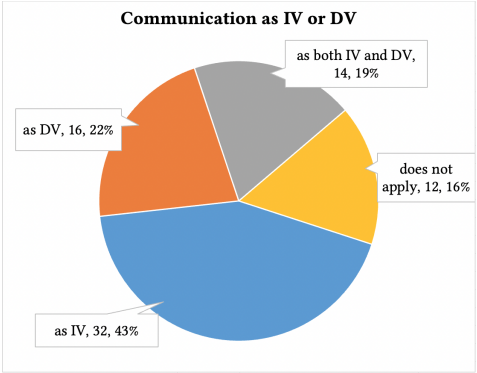

Fig. 5. Communication Examined as Independent or Dependent Variable(s) in HAT Research

4.1 How and What Do Humans and AI Teammates Communicate in HAT Research (RQ1)

4.1.1 Communication Modality. Text-based communication dominates HAT research, with over half of studies (58%) relying on chat interfaces or preset AI messages. This reflects a preference for controllable, easily logged interaction, but limits exploration of richer modalities. Multimodal approaches combining text with visuals are less common (14%), and only small shares use audio (9%, e.g., [59, 98, 115]), visual (4%, [16, 163, 192]), or behavioral cues (4%, [4, 67, 116]). Only six studies (8%, e.g., [14, 15, 91, 133, 149, 175]) explicitly manipulated modality, despite its recognized importance to effective teaming [197].

The limited use of behavioral or nonverbal signals (e.g., gestures, facial expressions) in the reviewed literature reflects prevailing design and measurement practices in interface-mediated HAT research rather than the absence of such cues in virtual systems. While nonverbal and behavioral communication can be realized in non-physically embodied agents, these channels are rarely operationalized or treated as core variables. As a result, modality is often treated as a matter of convenience rather than a core analytic dimension, leaving open questions about how different communicative channels shape coordination, workload, trust, and shared understanding in more naturalistic HAT interactions.

4.1.2 Communication Directionality. About half of studies (53%) enabled some form of bidirectional communication, though often superficially: in eight, AI could not actually respond to human input, creating an illusion of dialogue. Many others (25) relied on Wizard-of-Oz (WoZ) methods, raising concerns about generalizability to real-world systems. One-way communication, usually AI-to-human, appeared in 32% of studies and centered on transparency, explanations, or status updates. These positioned humans as passive recipients rather than partners, reflecting an instrumental view of communication. Only three studies manipulated communication directionality, leaving open questions about how genuine back-and-forth exchange shapes teaming in dynamic or ambiguous tasks.

4.1.3 AI Teammate Communication Behavior and Content. AI communication behaviors can be grouped into **information pushing** (AI provides updates, recommendations, or explanations) and **information pulling** (AI solicits human input). This distinction parallels models of proactive versus reactive agents [22] and reflects different assumptions about coordination in HATs. Information pushing encompasses informing (through status updates and alerts), recommending (by

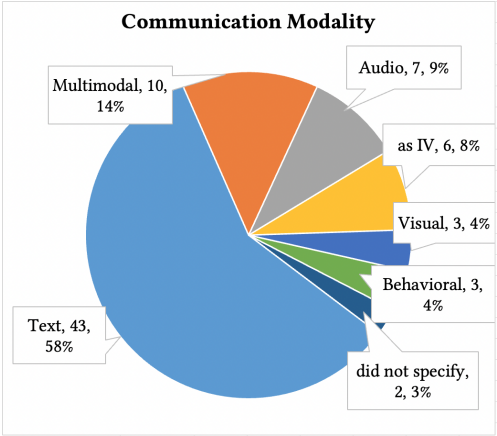

Fig. 6. HAT Communication Modality

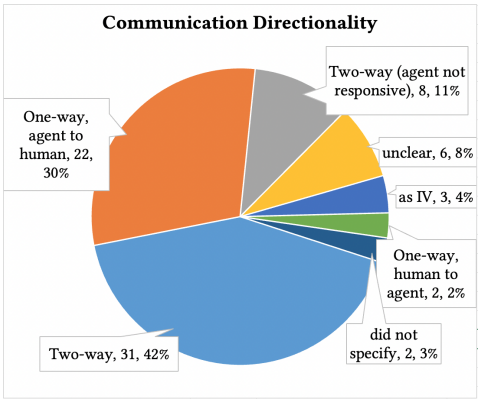

Fig. 7. HAT Communication Directionality

suggesting actions), and explaining (by providing rationales and apologies). Although often treated as interchangeable, these serve distinct cognitive and social functions. Information pulling is rarer but important for shared mental models: AI requests typically involve status checks or prompts for input, yet are rarely framed as active efforts to co-construct understanding. Table 2 summarizes this typology and examples of each.

Category	Sub-type	Example Focus and Citations
Information Pushing (AI provides information)	Inform	*Update own status and progress*: [3, 14, 15, 36, 42–48, 50, 73, 75, 76, 89, 102, 103, 130, 131, 149, 175, 176, 184, 196] *Warn, alert, hint, observations*: [3, 14–16, 110, 134, 136, 163, 169, 170, 179, 188, 190] *Communicate capabilities/confidence*: [110, 150, 167]
	Recommend	[5, 14–16, 66, 110, 121, 134, 163, 167, 169, 170, 175, 188–190, 192]
	Explain	*Apology, trust repair*: [150, 159, 198] *Rationale behind recommendations*: [87, 91, 110, 133, 179, 195]
	Other	*Social & emotional communication*: [88, 122]
Information Pulling (AI requests information)	Request for status/progress	[36, 42–48, 50, 73, 75, 76, 89, 102, 103, 130, 131]
	Request for confirmation	[84, 86, 191]
	Request for resources	[29, 30, 105, 157, 158]
	Request for clarification	[58, 59]
	Request for participation	[97, 98, 115]

Table 2. Types of AI-Initiated Communication in HAT Research

4.2 Communication as the Input in Experimental Research

4.2.1 *Operationalization of Communication as an Independent Variable* ***(RQ1a)***.

Operationalization of Communication Modality. Only a small subset of studies explicitly manipulated modality, usually comparing channels or interface designs. For example, Bogg et al. [14, 15] compared audio versus text, while Tokadli and Dorneich [175] compared centralized and distributed multimodal interfaces, showing that richer graphical feedback enhanced perceptions of the AI as a

teammate. Similarly, Mehrotra et al. [133] and Hauptman et al. [91] examined text versus text + visual explanations, embedding modality within broader transparency manipulations. Across these efforts, modality is often treated as a delivery mechanism, rather than a communicative act, and is rarely linked to task demands or team dynamics. This highlights an opportunity to theorize when and why certain modalities are appropriate, beyond testing performance outcomes.

Operationalization of Communication Directionality. A few studies varied directionality (i.e., who initiates or responds), moving beyond simple one- vs. two-way models. Ashktorab et al. [3] reversed human and AI roles in a guessing game to examine agency, while Chiou et al. [30] compared negotiated versus reciprocal exchanges. Wright et al. [191] contrasted directive (AI asks a question, human answers, interaction ends) with non-directive styles (AI responds to the human's interpretation), showing how directionality shapes interactivity and perceived authority. Collectively, this work links directionality to agency, control, and role symmetry, but still treats it as a binary affordance rather than a flexible design variable shaped by context or task demands.

Operationalization of AI's Communication Behavior and Content. Most manipulations center on what the AI communicates, usually under transparency [16, 134, 163, 179, 188–190] or explanation [91, 110, 150, 159, 179, 196]. Transparency often entails real-time displays of intent or confidence, while explanation is post-hoc or dialogic (e.g., rationales, trust repair) [25]. Implementations vary: some adjust message detail [16, 134], while others focus on repair strategies [159, 196]. These manipulations blur content and style, and few compare different communicative goals (e.g., persuasion vs. coordination). Message content is thus framed mainly as information, with limited attention to framing or timing as interactive dynamics.

Operationalization of Communication Failure and Absence. Several studies explored communication through its failure or absence. Seven (e.g., [43, 74, 75, 77, 89, 103, 104]) modeled comprehension failures, where AI misinterpreted input, or communication cuts, where human–AI channels were disabled to simulate infrastructure breakdowns. A smaller set manipulated communication presence as a binary condition. For example, Harbers et al. [87], Subramanian et al. [167] tested whether explanations or uncertainty cues improved trust, while McGee et al. [126], Tokadlı et al. [176] examined whether simply enabling voice or interface access affected performance, awareness, workload, and perceptions. These studies treat communication as a boundary condition that scaffolds or constrains teaming, but by operationalizing it as binary, they risk oversimplifying its complex and interactive role.

*4.2.2 Effects of Communication on Team Outcomes **(RQ1b)**.* We identified a wide range of outcomes of communication in HATs. The most common are **team performance** (33 studies; e.g., [36, 47, 73, 159, 195]), **trust** (25; e.g., [91, 130, 179, 189]), and **workload** (19; e.g., [46, 59, 134, 163]). Other frequently examined outcomes include situation awareness (15; e.g., [15, 74, 131]), perceptions of the AI teammate (9; e.g., [3, 97, 115]), and broader team experience (7; e.g., [58, 85, 183]). Less commonly studied are shared mental models (5; e.g., [85, 157, 158]), reliance (4; e.g., [179, 188, 195]), and other individual states (e.g., complacency [150], stress [188], conformity [188]). Many overlap conceptually (e.g., trust vs. reliance) yet are measured inconsistently, complicating comparisons. We therefore focus on the three most frequently examined outcomes to illustrate how communication shapes them and how measurement choices influence findings. Our analysis highlights both the central role of communication in performance and trust, and the field's uneven attention to its broader cognitive and experiential effects. We also map operationalizations of communication features (Section 4.2.1: modality, directionality, communication behavior/content, and failure/absence) to the team outcomes they were shown to affect, in Table 3.

Communication Feature Manipulated	Primary Outcomes Reported	Example Findings / Studies
Modality (audio vs. text; graphical vs. textual; multimodal interfaces)	Team performance, perceptions of AI teammate, workload	Richer graphical feedback improved perception of AI as teammate [175]; text+visual explanations enhanced trust compared to text-only [91, 133]; audio vs. text affected workload and awareness [14, 15].
Directionality (one-way vs. two-way; human vs. AI initiation; directive vs. non-directive)	Trust, team performance, perceptions of AI teammate	Non-directive bidirectional exchanges improved interactivity and balanced control [191]; reversing human/AI roles shifted perceptions of agency [3]; negotiated vs. reciprocal communication affected coordination quality [30].
AI Communication Behavior / Content (transparency, explanations, rationales, trust repair strategies)	Trust, workload, situation awareness, team performance	Transparency increased trust in some contexts [16, 134], but effects varied by trust type [179, 189]; explanation strategies supported trust repair and workload management [159, 196]; message detail influenced performance accuracy [16].
Communication Failure / Absence (misinterpretation, channel breakdowns, presence)	Team performance, trust, situation awareness, workload	AI comprehension failures degraded performance [44]; removing communication channels reduced awareness and increased workload [75, 104]; presence of even minimal communication, such as explanations, buffered trust [87, 167].

Table 3. Mapping of Human–AI Communication Features to Observed Team Outcomes in Experimental HAT Research

Team performance. Team performance is the most consistently studied outcome of human–AI communication. It is typically measured using objective indicators such as task completion, accuracy, and efficiency (e.g., [36, 47, 73]) or subjective self-reports (e.g., [87]). Across studies, AI information-pushing behaviors (e.g., updates, alerts, or recommendations) are generally linked to improved performance [45, 49]. By contrast, missed updates or comprehension failures can degrade performance [44]. Communication dynamics also matter temporally, as changes in one teammate's behavior can shift system performance over time [47]. Training humans to coordinate more effectively with AI (e.g., coordination training) further buffers against autonomy failures [102, 103].

Trust. Trust is central in HATs but inconsistently defined. Some studies treat AI as a teammate (using organizational trust scales, e.g., [124]), while others treat it as a tool (using system trust measures, e.g., [100]). These framings yield mixed results: transparency sometimes boosts trust [16, 134], but often shows null or measure-dependent effects [163, 179]. For example, Wohleber et al. [189] found transparency did not affect organizational trust but did improve system trust. Similar inconsistencies appear in explanation studies [110, 159], underscoring the need to clarify which trust type links to which communication form.

Workload. Findings on workload are mixed and shaped by the measure used. Subjective tools, such as NASA TLX, often show no effect of communication manipulations (e.g., transparency,

explanation) [163, 179], whereas objective indicators, like eye-tracking or physiological data, detect shifts more readily [190, 191]. Comparative studies also show AI–human teams report lower workload and communicate less than all-human teams [47], raising questions about whether this reflects efficiency gains or disengagement. Overall, communication may simultaneously reduce task demands while reshaping engagement and role distribution.

5 Influencers of Human-AI Communication in HATs

This section explores how various features of the research setup, such as AI characteristics, team size and composition, task type, and interaction environment affect communication in HATs. We begin by synthesizing how these contextual elements are represented across the full body of reviewed studies, regardless of method, to provide a broad overview of how communication is situated in HAT research. We then narrow our focus to experimental studies that treat communication as the dependent variable, examining how specific features of the setup are manipulated to investigate their impact on human-AI communication patterns. This two-part structure allows us to distinguish between the descriptive context in which communication occurs and the causal assumptions about what shapes it.

5.1 Contextual Features Shaping Communication Across HAT Research (RQ2)

Categories	Total	%
AI Control Method		
Wizard of Oz	28	38
Fully Autonomous	24	32
Pre-programmed Interface	14	19
Unclear	3	4
Vignette	2	3
As IV	1	1
NA	2	3
AI Visual Appearance		
No visual appearance	46	62
Avatar	21	28
Image	3	4
Unclear	2	3
NA	2	3
AI Role to Human		
Teammate (role distinctive from human)	23	31
Decision Support	20	27
Teammate (role similar to human)	13	18
Facilitator	6	8
As IV	4	5
Opponent	4	5
Partner	2	3
NA	2	3

Categories	Total	%
Team Size and Composition		
2 (HA)	43	59
3 (as IV)	12	16
3 (HHA)	10	14
3 (HAA)	2	3
4 (HHHA)	4	6
3–4 (HH(H)A)	1	1
more than 4 w/ one human	1	1
NA	2	3
Interaction Environment/Platform		
Simulation testbed	39	53
3rd party simulation builder	10	13
Video game	6	8
Web interface	6	8
Social/Dialogue platform	6	8
Video conferencing	5	7
NA	2	3
Task Type		
Type 8: Execute Performance Task	47	64
Type 4: Decision-making Task	8	11
Type 7: Contests/Battles	5	7
Type 3: Intellective Task	5	7
Type 1: Planning Task	3	4
Type 6: Mixed Motive Task	3	4
Type 2: Creativity Task	1	1
NA	2	3

Table 4. **Summary of the Characteristics of AI, Team, Task, and Environment.** For "Team Size and Composition," H stands for human and A stands for agent.

5.1.1 ***Agent Control Method.*** We categorized the methods used to implement or simulate human–AI interaction into six groups: 1) Studies using the Wizard of Oz paradigm [41, 152], in which participants believed they were interacting with a real AI agent, when in fact the responses were

generated by a trained human confederate. 2) Fully Autonomous: Studies involving AI agents that operated independently without human control. 3) Pre-Programmed Interface: Studies using scripted interfaces where participants interacted by reading AI-generated information and responding through constrained input options (e.g., multiple-choice selections or button clicks), rather than through dynamic communication. 4) Vignette-Based Simulation: Studies that employed video or scripted depictions of AI-human interactions to manipulate perceptions of communication behavior without actual interaction. 5) Studies that manipulated the AI control method as an independent variable (e.g., comparing WoZ vs. autonomous agents). 6) Unclear: Studies that did not provide sufficient methodological detail to determine the AI control method. For two studies without experimental manipulations, these categories were marked as Not Applicable (NA).

Control method sets the boundaries of what an AI teammate can communicate. WoZ designs allow natural language exchange, supporting insights into dyadic and team-level patterns and into how humans anthropomorphize versus objectify AI partners [36, 73]. Yet WoZ flexibility may exceed real AI capabilities, risking distorted conclusions about communication in applied settings.

5.1.2 ***Agent Visual Appearance or Representation.*** Most studies (62%) used agents without visual representation, suggesting embodiment is often treated as unnecessary in HATs. In contrast, 28% employed avatars to convey presence, movements, or actions, with designs ranging from humanoid (n=11) and robotic (n=5) to symbolic (n=5). Fourteen avatars were animated, seven static. A smaller set (4%) paired static images with text [133, 150, 195], minimizing social presence. These variations highlight inconsistent treatment of visual representation, often framed as an aesthetic or interface detail, rather than a core component of communicative engagement.

Visual representation shapes both social perception and communicative affordances. Agents without embodiment are limited to verbal channels, excluding cues like gaze, gesture, or spatial positioning that support coordination and joint attention. By contrast, 3D humanoid or robotic avatars [67, 84–86, 110, 149, 159, 196] enable richer nonverbal behaviors and allow systematic manipulation of social identity cues (e.g., gender, race, age) to study their effects on trust, bias, and team dynamics. Even simplified 2D or symbolic avatars can convey agent status or activity in shared spaces [158, 179], balancing clarity with low cognitive load. Collectively, these findings suggest embodiment is not an aesthetic choice but a functional dimension of multimodal communication, though its role remains under-theorized in HAT models.

Notably, visual gendering is patterned: military-task agents are almost always embodied as male [149, 159, 196, 198], while facilitator agents appear as female [58, 59, 115]. Such choices may affect communication, as people often ascribe gender-specific expertise to robots and adjust dialogue accordingly [54, 148]. Other anthropomorphic features (e.g., age, race) may similarly shape communication through accommodation processes [72].

Beyond shaping communication dynamics, patterns in AI representation raise important inclusivity and ethical considerations for HAT research and design. The consistent pairing of male-presenting agents with military-task and female-presenting agents with facilitation or support roles risks reproducing and normalizing gender stereotypes in collaborative work [53]. Such representational choices may shape not only humans' expectations of AI competence and authority, but also whose communication styles are privileged or marginalized in team interactions. Future HAT research should therefore more deliberately vary and justify agent representations, attend to how demographic cues intersect with role, power, and communication behavior, and reflect on the downstream implications for inclusive system design [7].

5.1.3 ***Agent Role in Relation to Human(s).*** In HAT research, AI agents are often framed as teammates [131], though their roles vary along two dimensions: **relational framing** (e.g., peer, opponent, partner) and **functional contribution** (e.g., executing tasks, advising, facilitating).

Extending prior work on robotic roles [161], we identified six categories. Most studies frame the AI as a **Teammate**, either role-differentiated [46, 73] or role-symmetric [67, 196]. About a quarter positioned the AI in **Decision Support**, offering recommendations or analyses without direct task execution. Although functionally limited, these agents were framed as proactive systems capable of independent reasoning, thereby shaping human perceptions of the AI as an autonomous teammate rather than a passive tool. A smaller subset depicted the AI as a **Facilitator** of human–human collaboration (e.g., [97]), an **Opponent** in competitive tasks [3, 4], or a **Partner** outside the team (e.g., neighboring hospital) [29, 30]. A few studies have directly manipulated role (e.g., tool vs. teammate [5, 184]), underscoring the interest in how framing shapes dynamics. While "teammate" is the dominant label, many roles align more with support systems, facilitators, or adversaries, raising questions about what true "teaming" entails.

The AI's role also shapes communication expectations. First, humans are more receptive of the AI teammate in assistive roles, where the AI reports to them, as shown in collaborative gaming contexts [3, 199]. Second, role framing influences not just whether the AI communicates but how (e.g., its style, content, and volume [9, 18]). For instance, lower-status roles may be expected to communicate more submissively, while higher-status roles may warrant assertiveness [18]. Metaphors used to describe the AI (e.g., "trained professional" vs. "fresh graduate") further induce different communication expectations [109].

5.1.4 ***Team Size and Composition.*** Most HAT communication studies (59%) used dyads. Twenty-four (34%) examined three-member teams, with ten (14%) involving two humans and one AI (HHA) and two (3%) with one human and two AIs (HAA). Four studies (6%) tested four-member teams of three humans and one AI (HHHA) [58, 59, 98, 115]. One used variable human–AI groups of three to four members [88], and another studied large teams of 6–8 members with one human, one manipulated AI, and 4–6 unmanipulated AIs [122]. Twelve studies (16%) explicitly treated team composition as an independent variable.

Team size and composition shape communication dynamics. While dyads allow simplified exchanges, larger teams face coordination challenges such as turn-taking [153] and interruption [164], which affect efficiency and cognitive load [65, 81]. Yet most multi-member studies still used only one communicative AI, typically broadcasting the same message to all members. In practice, multiple AI teammates may fill distinct roles [68], requiring differentiated communication beyond simple broadcasting.

5.1.5 ***Team Interaction Environments.*** Over half of studies (53%) used custom-built simulation testbeds, most commonly the CERTT-UAV-STE (18 papers) [36, 38, 46, 73, 75, 130]. Another 13% leveraged third-party engines such as Unity [84–86, 110] or Unreal [191], while six used customizable video games (e.g., Arma, Rocket League, Netrek) [67, 122, 159, 196]. Six relied on simple web interfaces, and five integrated AI into video conferencing platforms [58, 59, 88, 98, 115].

Simulation testbeds offer strong experimental control but constrain communication: interactions are typically rigid, templated, and context-specific. Findings such as the predictive ratio of information push vs. pull in CERTT environments [45, 49, 73] may not generalize to real-world HATs or replicate across platforms.

5.1.6 ***Team Task Types.*** We categorized tasks using McGrath [127]'s Circumplex Model, which distinguishes eight types across generative, decision, negotiation, and execution domains. Most studies fell into **Type 8: Performance/Psychomotor tasks**, reflecting execution-heavy military simulations where coordination and tool use are central [186]. Decision-making tasks (**Type 4**) comprised 11%, while contests (**Type 7**) and intellective problem-solving (**Type 3**) each accounted for 7%. Planning (**Type 1**) and mixed-motive (**Type 6**) tasks appeared in 4% each, and only one

study used a creativity task (**Type 2**). Overall, HAT research remains concentrated on operational execution, with limited exploration of generative, creative, or negotiation-based collaboration.

5.2 Communication as the Outcome: Factors and Measures of Communication in Experimental Research

*5.2.1 Measuring Communication as a Dependent Variable **(RQ2a)**.* Thirty studies examined communication as a dependent variable, with over half concentrated in the CERTT simulation environment. Seventeen used the same detailed coding scheme to categorize text-based communication into eight coordination-relevant types (e.g., status updates, planning, inquiries). This framework provides granular insights into message function but raises concerns about methodological homogeneity and limited generalizability. Some CERTT studies extended the approach by analyzing temporal dynamics (e.g., timing, directionality) [43, 46, 47, 73], and one examined anthropomorphism in language use [36].

Outside this group, most studies relied on simple message frequency counts [5, 43, 104, 158, 179, 183, 184]. While easier to implement, such metrics overlook content and function, risking oversimplification of interaction. Overall, the field depends heavily on a narrow set of strategies, underscoring the need for more diverse, theoretically grounded measures to capture the richness of human–AI communication.

*5.2.2 Factors That Influence Communication in HATs **(RQ2b)**.* Independent variables influencing communication cluster around two themes: team composition and communication failures (Table 5). Team composition studies compared human-only and human–AI groups, revealing inconsistent results: even within the same platform, outcomes diverged on performance and communication dynamics [43, 44, 131, 158]. These inconsistencies suggest composition effects depend on task structure, teammate expertise, and communication expectations.

Studies of AI communication failures show that failure types matter: comprehension errors often trigger increased information pushing, whereas communication cuts do not [89]. Adaptability improves when teams receive pre-task training [102], but failures are usually framed as functional disruptions, with little attention to their interactional or meaning-making implications [34].

By contrast, factors such as AI role, modality, directionality, and task interdependence have been sparsely examined (one to three studies each). Other central constructs (e.g., AI autonomy, communication style, or training) are rarely manipulated. Null effects for variables like directionality [191] raise questions about how these factors are operationalized and whether current task designs are sensitive enough to detect their influence.

In sum, the literature overrepresents a narrow set of experimental paradigms while underexploring theoretically rich and ecologically relevant constructs. Future work should diversify factors, adopt multi-factorial designs, and align more closely with integrated models of team interaction.

6 Discussion

Our review has thus far synthesized how and what do humans and AI teammates communicate in existing HAT research (**RQ1**), focusing on the modalities, directionalities, content and behaviors. Viewing communication as an **input**, we examined how it has been operationalized as independent variables (**RQ1a**) and its impacts on various team outcomes (**RQ1b**) in experimental studies. Conceptualizing communication as an **outcome**, we critically reflected on how current methodological approaches in HAT research may shape, constrain, or skew our understanding of communication in HATs (**RQ2**). We also reviewed how communication is commonly measured (**RQ2a**) and the factors found to influence it (**RQ2b**) in experimental settings. The contributions made by the reviewed research on HATs provide a starting point to drive the field forward by highlighting areas of

Independent Variables Examined to Impact Human-AI Communication	Number of Studies	Example
Team composition	13	[42–47, 49, 73, 131, 136, 158, 183, 184]
AI comprehension failure	8	[36, 43, 46, 47, 75, 89, 102, 103]
Communication cut	8	[36, 43, 46, 47, 75, 89, 102, 103]
Team performance	4	[74, 77, 89, 130]
AI's role in relation to human	3	[5, 183, 184]
Training type	2	[102, 103]
AI's levels of autonomy	1	[104]
Task interdependence	1	[179]
Communication directionality	1	[191]
Task load	1	[191]
Communication modality	1	[126]
Communication behavior	1	[179]

Table 5. Factors Examined to Impact Human-AI Communication

communication that are under-explored, in order to conceptualize and theorize about communication in HATs, and to provide practical guidelines for designing AI teammates with optimal and adaptive communication capabilities. In light of these, we discuss this review's implications for future research in terms of theory, methodology, and design (see Table 6 for a summary of all the gaps and recommendations for future work).

6.1 Theoretical Implications

As HAT research expands, there is a growing need for theory that specifically accounts for how communication operates in HATs. Two factors are central to such theorizing: the nature of teamwork and the **positioning** of AI within the team. In this section, we draw on theories of human teams and human–computer interaction, together with findings from our review, to propose an updated input-process-output (IPO) framework to encapsulate the involvement of communication across all stages of IPO, for guiding future research efforts.

6.1.1 Reconceptualizing Communication in HATs in light of Human Team and HCI Theories. Communication in human teams is heavily influenced by a process referred to as **social categorization**, where individuals group themselves and others into social categories, often based on shared demographics, professional backgrounds, etc. [171]. Perceived in- and out-group membership has been found to impact teammates' communication behaviors [129], willingness and comfort to interact with one another [177], to share information [194], and to cooperate [32], which consequently affects group cohesion, polarization, and future intention to work with each other [193]. Emerging HAT research suggests that similar processes may already be at play when AI is introduced as a teammate. For example, Duan et al. [60] demonstrates that trust and distrust can spread within HATs through social processes such as factionalism and in-group favoritism, with humans dynamically reclassifying AI teammates based on how they communicate about and relate to other team members.

Focus	Identified Gap	Targeted Recommendation
Theory	Limited theorization of communication in HATs beyond task performance	Develop theories that account for both taskwork and teamwork, linking cognitive and social processes (e.g., cohesion, power, equity).
	Ambiguity in positioning AI as tool, medium, or teammate	Advance perspectives that treat AI as communicative actors, drawing on CASA and human team theories.
	Lack of process models of communication	Apply and extend frameworks such as IPO and conversational grounding to model communication dynamics over time.
Method	Over-reliance on experimental settings (98%), limiting ecological validity	Use qualitative and ethnographic approaches (e.g., interviews, fieldwork) to uncover real-world communication needs.
	Narrow focus on text or voice channels	Expand to multimodal communication (visual, haptic, behavioral), and examine trade-offs across modalities.
	Limited exploration of socio-emotional communication	Investigate affective and relational communication (e.g., cohesion, trust, team morale) alongside task-focused exchanges.
	Simplistic operationalization (frequency counts, presence/absence)	Diversify measures (turn-taking, interruptions, backchanneling, emotional tone), combining subjective, observational, and automated methods.
Design	HAT systems often separate communication from taskwork and overlook its role in shaping teamwork.	Integrate communication purposefully and responsibly: embed two-way, role-sensitive dialogue into unfolding taskwork; tailor communication to AI's functional expertise and social role, and tools to monitor team dynamics over time to ensure goal alignment.
	Communication in HATs is often mechanical, lacking collaborative grounding needed for complex and high-stakes teamwork.	Treat communication as an iterative grounding process: use interactive dialogue (clarification requests, backchannels, adaptive signals), provide configurable protocols for when AI should seek clarification, and train teams to share grounding responsibility.

Table 6. Summary of theoretical, methodological, and design gaps in HAT communication research with targeted recommendations.

Social exchange process [12] plays a significant role in shaping team interactions, collaboration, and trust [39]. For instance, team members share information and resources and assist each other

with tasks, expecting to receive a similar level of honesty and support in return [142]. They also reciprocate self-disclosing behaviors and vulnerability [172] to share intimate information, which further enhances team cohesion [119]. These patterns raise important questions for HATs regarding whether and how similar forms of communicative reciprocity emerge between human and AI teammates.

While HCI, computer-mediated communication (CMC), and CSCW all study technology and communication, they have historically differed in how technology is **positioned** within interaction. CSCW has often conceptualized technology as a medium that supports communication between humans [80, 111, 168], whereas HCI research has more directly examined computers as interactive and communicative entities. As AI systems increasingly initiate dialogue, respond contingently, and participate in team coordination, treating technology solely as a passive medium becomes insufficient. Our review suggests the need to more explicitly theorize AI as a communicative actor within team interaction [55, 98, 115], rather than only as a channel through which human communication occurs.

In HCI, the **computers-are-social-actors (CASA)** paradigm [141] demonstrates that people routinely apply social expectations and norms to computerized agents, including stereotyping, politeness, and reciprocity [69, 112, 139, 140]. Prior to the emergence of human-AI teaming, Nass et al. [138] showed that computers could be perceived as teammates when team affiliation was meaningfully structured, shaping perceived similarity, information quality, and openness to influence. Research in our review extends these insights to HATs, showing that social categorization dynamics influence communication. For example, Hwang and Won [98] found that same-gender AI agents increased participation among minority women, echoing patterns observed in human teams [137]. These findings position CASA as a useful framework for understanding how AI teammates participate in, and potentially shape social and communicative processes in HATs.

6.1.2 An IPO Framework for Conceptualizing and Researching Communication in HATs. Drawing on this review and prior work on human teams and HCI, we propose an input–process–output (IPO) framework [82] to characterize how communication has been studied in HATs and to guide future research. As shown in Figure 8, communication spans all three stages of the model. However, most existing HAT research adopts a functional input–output perspective [187], overlooking the communicative processes that transform inputs into outcomes. Our framework foregrounds communication as both an input and an emergent process shaping team outcomes.

Regarding communication as input, work included in this review shows that communication modality, directionality, and AI communication behaviors (e.g., transparency and explanation) shape taskwork outcomes such as performance and trust in AI [3, 15, 110, 163, 179, 188]. These findings highlight the need to move beyond task performance to examine **teamwork outcomes**. For instance, concepts such as trust are multifaceted, involving not only the evaluation of teammates' task-related capability but also their sociability traits (e.g., integrity and benevolence) [123, 125]. Additionally, such findings also motivate distinguishing outcomes by **level of analysis**, as individual-level performance or trust does not necessarily translate to team-level effectiveness or cohesion. Accordingly, we categorize outcomes by taskwork versus teamwork and by individual- versus team-level (Figure 8).

Regarding communication as output, our review shows that team composition (e.g., replacing a human with an AI teammate) and the AI's role relative to humans shape the frequency and directionality of communication in HATs [42, 132, 158, 183]. Beyond these factors, theories from human teams and HCI suggest that characteristics of the AI, team structure, task, and context can further influence how communication unfolds and with what consequences. For example, AI appearance cues (e.g., gender or age) can trigger social categorization processes that shape

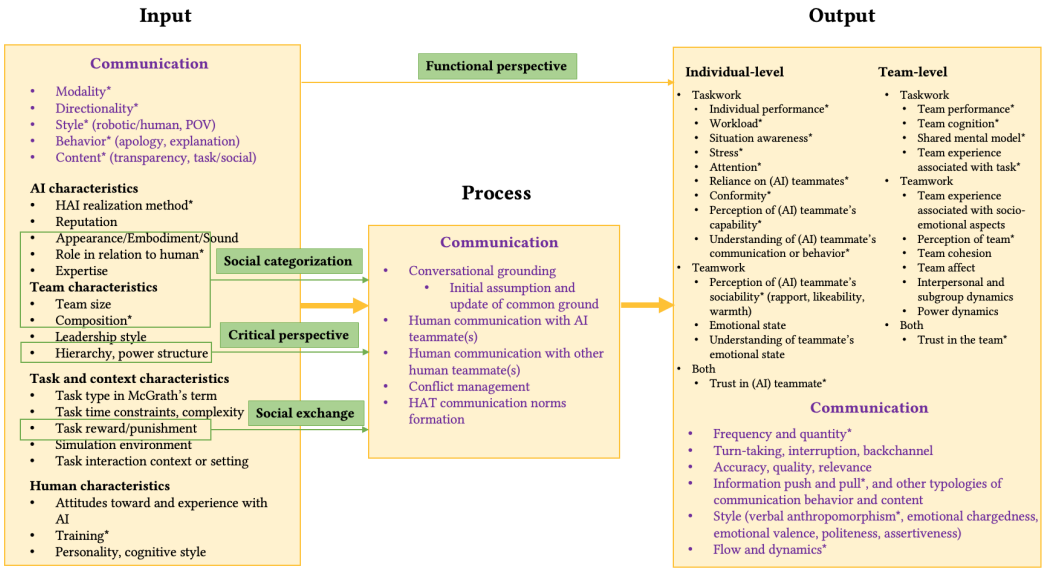

Fig. 8. An Input-Process-Output Framework for Conceptualizing and Researching Communication in Human-AI Teams. (Factors and outcomes that have been examined in existing HAT research included in this review are denoted with an asterik (*)

initial trust and communicative openness, and have been leveraged to improve minority members' participation [98, 120, 141, 171, 180]. More broadly, team hierarchies, power relations, and incentive structures may both shape and be reshaped by communication in HATs, motivating analysis of communication outputs as socially embedded and context-dependent (Figure 8) [6, 12].

Communication as a process remains largely under-examined in HAT research, with few exceptions highlighting the role of proactive communication and the emergence of interaction norms over time [196]. From a communication-as-collaboration perspective, a key open question concerns how conversational grounding unfolds between humans and AI, specifically how assumptions about common ground are formed, updated, and sometimes misaligned as AI becomes increasingly capable of natural language interaction [33]. Beyond human–AI exchanges, initial evidence suggests that AI and team characteristics also shape how humans perceive and communicate with one another [98, 158]. From a temporal perspective, HAT communication evolves as teams develop norms, make sense of behavior and context, and manage conflict, underscoring the need to examine how communicative processes and social dynamics co-evolve over time [62, 128, 173, 178].

6.2 Research Gaps and Directions for Future Work - Methodological Implications

6.2.1 Leveraging Qualitative and Ethnographic Research Methodologies to Identify the Actual Communication Needs in HATs. Our review suggests that almost all (98%) of the HAT research involving communication was conducted using an experimental approach, among which the qualitative reflections were also based on the interaction during an experiment. Experimental settings provide control over the variables of interest to establish causal relationships and offer participants a grounded experience for reflection. However, communication in these artificial settings is highly context-specific, and may not reflect the types of communication needed in the real-world work environments. In the medical domain, for instance, AI was found to better adapt its communication to different clinicians of various demographics [20]. For Cyber Security Incident Response Teams,

AI is even expected to dynamically adapt its level of autonomy and communication at various stages [92]. With rapid advancements in large language models (LLMs) integrated into organizations across various sectors [94], human-AI teaming in these organizational contexts will inevitably be shaped by the technology, fostering novel communication practices, dynamics and cultures that have never been present before. As such, future work should leverage qualitative methods such as individual or focus group interviews, ethnography, and other grounded theory approaches to first identify the communication needs in HATs, in ways similar to [90] that interviewed professionals whose jobs involve collaborating with AI on a daily basis to identify what makes an AI a trustworthy colleague. Additionally, ethnographic methodology [151] provides a useful tool for AI and HCI researchers to gain a first-hand, nuanced, and dynamic understanding of how communication practices form and develop within a team and across teams in their natural work settings.

6.2.2 Diversifying Communication Affordance, Behavior, and Content. Most existing studies have primarily focused on text-based chat or voice communication, which fail to capture the richness and diversity of communication in real-world team interactions. There is a need to explore and incorporate alternative modalities, such as visual cues, haptic feedback, and multimodal approaches that resemble natural human communication. Future HAT research should also investigate the trade-offs associated with different communication modalities. For example, recent work by Zhang et al. [197] found that while visual communication reduced workload and improved team performance, it lacked the interactivity and interpersonal connection provided by verbal communication through text chat. Exploring these trade-offs can provide deeper insights into optimizing communication strategies and better tailoring them to meet the unique needs of diverse HAT applications.

The prevailing focus on basic information pushing (providing information) and pulling (requesting information) limits our understanding of AI's potential as a teammate. Future HAT research should allow the AI agent to communicate beyond task-related information and contribute to teamwork, such as inter-member relationships, team affect, cohesion, and trust [56]. This review suggests that aside from two exceptions [88, 122], very few HAT research has explored AI's socio-emotional communication. Admittedly, AI is primarily integrated into teams to enhance taskwork. However, humans are essentially social beings and tend to perceive machines as social beings as well [141]. In human teams, even purely task-related behavior can be interpreted as social. In fact, recent work [35, 106] suggests that the robot's resource allocation behavior, which is not intended to be social, can evoke social perceptions in humans. Affective communication also needs to be investigated in HATs, as one member's emotional state can be contagious to the entire team to influence the taskwork collaboration and team morale [8, 108]. Despite some progress on leveraging AI to regulate individual's emotions [71, 113], affective or emotional communication of AI has rarely been studied in teams (with very few exceptions such as [10]).

Additionally, beyond simple information pushing and pulling, AI agents should actively participate in the collaborative process of communication. Human communication is inherently collaborative and involves a process known as grounding [33, 34], where both parties work together to ensure mutual understanding. In this process, communicators must coordinate the content and process to ensure that what is communicated is understood as intended. To coordinate on content, communicators often start by assuming a level of shared information or common ground, which requires anticipation of what the addressee knows [70], often based on community co-membership (e.g., HCI researchers would know what CSCW stands for), linguistic co-presence (e.g., use a pronoun to refer to someone previously mentioned), and physical co-presence (e.g., referring to an object by pointing). And to coordinate on process, communicators need to update their common ground moment by moment, which requires the use of backchanneling [83] devices to acknowledge understanding (e.g., "uh huh", "right", nodding, etc.), or indicate a lack of understanding (e.g.,

"sorry?"). Blomsma et al. [13] found that backchannel behavior influenced the perceived personality of AI partners. While these are common in personal and home devices [31, 99, 118] and most recent text-based generative AI tools (e.g., ChatGPT), HAT research rarely implements these. In HRI, this is slightly more explored. For instance, Jung et al. [107] found that verbal and nonverbal backchanneling from a robot improved team functioning and perception of robot's engagement.

6.2.3 Diversifying Ways of Operationalization and Measurement of Communication. With most HAT research examines communication only in terms of frequency and quantity, and presence or absence, this review also highlights the need for a more nuanced approach to diversifying communication operationalization and measurement. Besides common quantity metrics such as message counts, communication can be measured by the duration, turn-taking, backchanneling, and interruption behaviors to gain insights into the dynamics of HAT communication potentially impacted by other variables such as the AI's appearance, perceived power and expertise, team composition, etc. through various social processes. Future HAT research can also use quality metrics such as information clarity and relevance, content metrics such as emotional tone, collected through a wide range of subjective, observational, or automated methods.

6.3 Designing Role- and Team-Sensitive Communication for HATs

6.3.1 Purposeful and Responsible Integration of Communication into Human-AI Taskwork and Teamwork. Although HAT research emphasizes task execution, most systems lack bidirectional and interactive communication, resulting in parallel rather than integrated trajectories. Integration of communication and task execution often relies on Wizard-of-Oz or command-and-control interfaces reminiscent of pre-AI machine operation. Future HATs must closely integrate two-way and even multi-way natural language communication into team task execution to create a team collaboration experience that is more natural for humans [199]. This poses challenges in context understanding [166], managing miscommunication in complex tasks [93, 185], and addressing linguistic and cultural diversity in teams [57, 115]. Addressing these challenges will require technical advances alongside interdisciplinary insights from CSCW and NLP, to ensure the communication feels both natural for humans and computationally straightforward and efficient for AI systems.

For design practice, HATs require communication that is embedded in task execution, adaptive to team roles, and coordinated across multiple humans and AI. Systems should support dynamic dialogue that aligns with task demands, manages turn-taking, and synchronizes role-specific updates to prevent overload. Communication must adapt to the AI's functional expertise, whether mirroring human expertise (e.g., an analyst cross-checking sensor data), complementing it (e.g., a navigator providing spatial updates to a pilot), or contributing from a distinct role (e.g., a monitoring agent flagging anomalies). Additionally, AI communication should also reflect its social role on the team: as a facilitator, summarizing discussions or surfacing overlooked contributions; as an assistant, offering just-in-time recommendations while deferring final authority; or as a leader, issuing directives and coordinating resources. Communication modalities should also complement one another by combining concise visual or haptic cues with language to reinforce coordination without disrupting task flow. At the organizational level, training should prepare human teammates to interpret and act on AI communications within the flow of task execution, ensuring that information is integrated into collective work processes rather than treated as peripheral or optional.

Moreover, purposeful integration at the task-level must be matched with **responsible integration at the teamwork level**. Team communication shapes not only cognitive processes but also social dynamics such as team cohesion and power relations [8, 39, 129]. Our review suggests that AI communication can help rebalance teamwork, such as mitigating discomfort from gender

imbalance [98] and cultural-linguistic disparities [59, 115], yet they also risk reinforcing stereotypes or fostering unhealthy dependencies [54]. Similarly, communication designed to promote equity may unintentionally mask deeper systemic issues [160]. These observations underscore that communication design in HATs is never neutral. Decisions about how AI communicates, such as whose contributions are highlighted and how norms are reinforced, can differentially shape participation, voice, and power for team members with varying gender, cultural, or linguistic backgrounds. Responsible integration, therefore, requires designers and researchers to treat communication as a socio-technical mechanism that can either reproduce existing power asymmetries or actively support more inclusive and equitable collaboration. Making these design assumptions explicit and evaluating their downstream social effects is essential for ethically grounded HAT research and deployment. Future designs should therefore treat AI communication not just as a technical feature, but as a mechanism capable of shaping and shifting interpersonal and team norms [35], leveraging this potential while critically accounting for long-term impacts on perceptions and behaviors [96, 182].

We propose several practical design strategies for teamwork communication. First, embed transparency into socio-relational human-AI communication so team members understand why and how AI is engaging in social dynamics. For example, clarifying that a prompt to include a quieter member is based on observed participation gaps, or that a language reformulation is intended to bridge cultural-linguistic differences. Such transparency helps team members interpret the AI's communication as supportive of cohesion rather than intrusions. Second, design mechanisms should include configurable levels of communicative assertiveness and social proactivity, tailored to the AI's social role. For example, an AI acting as a facilitator might promote inclusion without dominating, whereas a mediator or leader might take on a more directive role in addressing imbalances within the team. Third, systems should enable teams to monitor and reflect on how human–AI communication shapes group dynamics over time by providing quantifiable indicators and retrospective visualizations (e.g., tracking shifts in speaking time, directive patterns, reliance on AI), with LLM-powered summaries highlighting emerging issues of trust, authority, bias, or dependency, allowing teams and organizations to align communication dynamics with team and organizational goals. Finally, policies should ensure that AI-mediated efforts to improve inclusion or balance power relations complement, rather than replace, structural and cultural initiatives. By designing teamwork communication in this way, HATs can enhance collaboration while remaining attentive to long-term social and ethical implications.

6.3.2 Human-AI Communication as a Collaborative Grounding Process. Current HAT research rarely treats communication as a collaborative process of grounding [33]. Instead, exchanges are often mechanical, sufficient for routine tasks but inadequate for complex team collaboration, where the establishment of common ground [33] is essential, requiring not only aligning initial assumptions about the AI's capabilities and intentions but also ensuring ongoing, accurate interpretation and acceptance of shared information to prevent miscommunication. Misalignment between AI knowledge and human expectations of its knowledge exacerbates this gap [199]. Advances in generative AI, such as prompt engineering [27], can help bridge this divide, but must be framed as iterative, two-way processes rather than one-sided techniques. From a grounding perspective, AI systems should support clarification requests, backchannels, and other mechanisms for mutual understanding [13, 107].

For design practice, this suggests several concrete directions. First, system designers should move beyond static explanation or transparency features [61] toward interactive dialogue mechanisms that allow both humans and AI to confirm shared understanding in real-time. For example, AI teammates could incorporate lightweight backchannel cues, such as acknowledgments, status

signals, or adaptive visual icons, that indicate receipt and interpretation of information. Second, organizational deployments of HATs should include configurable communication protocols that allow teams to decide when and how AI systems should ask for clarification, reducing risks of either disruption or silent errors. Third, policy and training efforts should prepare human team members to interpret and respond to AI communication, ensuring that collaborative grounding is seen as a mutual responsibility rather than a purely technical function. Together, these steps can make grounding a practical design principle in HATs, enabling richer, more effective team communication.

These design directions take on particular urgency when we consider how HAT communication unfolds across different domains. While previous work has shown that dialogue systems can enhance common ground in human-robot teams [23], extending these communication practices to HATs across diverse domains remains an open challenge. Our review highlights that most HAT systems treat communication as mechanical rather than collaborative, which limits their ability to scale to real-world contexts where grounding is critical. In healthcare, breakdowns in human–AI dialogue can have severe consequences [79]; in urban planning, systems must negotiate meaning among multiple stakeholders with differing perspectives [155]; and in education, they must adapt communication to support inclusivity and diverse learning needs [19–21, 165, 181]. Addressing these challenges requires designing HAT communication that actively supports clarification, backchanneling, and iterative feedback, while also providing configurable protocols so teams can decide when and how AI should intervene. Future CSCW research should therefore focus on developing communication mechanisms that enable shared understanding and resilience in high-stakes, multi-stakeholder environments, rather than limiting design goals to efficiency alone.

7 Conclusion

As AI becomes increasingly capable of communicating with humans in natural language and complementing human skills in various team settings, our understanding of communication in HATs urgently needs to keep pace with these technological advancements. This systematic review of the current landscape of HAT research involving communication provides a structured overview of how the characteristics of the AI, the team, the task and context shape the communication affordance, behavior and content, synthesizes the ways communication has been operationalized and measured, and the influencing factors of communication and how communication impacts other team processes and outcomes. Findings from this review inform the development of a theoretical framework that further guides future research and practice in advancing the understanding and design of communication in HATs.

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Received 13 May 2025; revised 13 January 2026; accepted 17 March 2026