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Reconceptualizing Activity Theory for Human-AI Teaming in Computer-Supported Collaborative Learning

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Abstract: The rise of artificial intelligence (AI) and large language models (LLMs) are reshaping the role of technology in Computer-Supported Collaborative Learning (CSCL). Once viewed as mediating tools, AI systems can now act as active teammates that co-construct meaning, share responsibility, and influence team cognition. This paper addresses the lack of theoretical grounding in existing human-AI teaming research by reconceptualizing Engeström's Activity Theory. Specifically, we extend the six components of the activity system (subject, tool, rules, community, division of labor, and object) to account for AI's dual role as both tool and quasi-subject within collaborative learning activities. Through this theoretical mapping, we highlight emerging questions for future research, including but not limited to issues of learner agency, trust, equity, and epistemic alignment. We conclude with a call for the CSCL community to revisit and expand its theoretical frameworks to better capture the evolving dynamics of human-AI teaming.

Introduction

While technology has long been a central component of Computer-Supported Collaborative Learning (CSCL), it has traditionally functioned as a *mediating artifact*, facilitating communication, coordination, and shared understanding among human learners without directly contributing to the discourse (Jeong & Hmelo-Silver, 2012). However, recent advancement in artificial intelligence (AI), particularly in large language models (LLMs), have fundamentally transformed this dynamic. That is, AI is no longer confined to the role of a *passive* tool but can now participate as an *active* teammate, co-constructing meaning, generating ideas, and contributing to both cognitive and social dimensions of collaboration. This emerging paradigm, also known as human-AI teaming, reconceptualizes the very foundations of CSCL, as AI teammates begin to assume team-level responsibilities, engage in decision-making processes, and influence the direction and quality of collaborative learning.

Despite the growing body of research on human-AI teaming, much of the current work has been technologically or empirically driven, focusing on design innovations (e.g., Chen et al., 2025), task performance (e.g., Flathmann et al., 2023), and user engagement and trust (e.g., Duan et al., 2025). For example, Choi et al. (2025) examined how AI teammates can reshape socio-cognitive dynamics of collaborative problem solving by examining discourse collected from experiments. While human-AI teaming research remains a nascent domain within CSCL, these studies often lack a comprehensive theoretical framework for understanding how collaboration with AI teammates transform the dynamics of group interaction, knowledge co-construction, and goal orientation. Without such conceptual grounding, we risk treating AI merely as an additional actor within existing collaborative systems rather than interrogating how its presence may reorganize the social, cognitive, and cultural structures of learning. In other words, there is a pressing need for a framework that captures the systemic, mediated, and evolving nature of Human-AI teaming dynamics.

To address this gap, this paper reconceptualizes a seminal theory used to understand collaboration in CSCL, namely Activity Theory. Originated from the socio-cultural work of Vygotsky and Leontiev and later expanded by Engeström, Activity Theory provides a systemic lens for analyzing how human actions are mediated by cultural tools, social rules, and collective goals (Barab et al., 2013). In CSCL research, Activity Theory has been used to examine how interactions among learners, teachers, and mediating artifacts shape the process of collaboration and knowledge construction (Collis & Margaryan, 2004; Hmelo-Silver & Chernobilsky, 2012). Building on this, we extend Activity Theory to conceptualize AI not merely as a tool but as a *quasi-subject* that participates in and transforms the collaborative activity system. Specifically, we aim to map the six components of Engeström's activity system – subject, tools, rules, community, division of labor, and object – to the context of human-AI teaming, and to compare how these relationships and tensions within the activity system differ from those in traditional human-human collaboration. Through this reconceptualization, we aim to highlight how the integration of AI teammates in CSCL reorganizes the fundamental structure and dynamics of collaborative learning activity.

The subsequent sections of the paper are organized as follows. We first provide a brief overview of human-AI teaming and Activity Theory, focusing on Engeström's expansion of the framework. We then present our conceptual mapping of Activity System components to human-AI teaming, highlighting key differences from traditional human-human collaboration. Finally, we discuss emerging research directions and critical questions for future inquiry into human-AI collaboration in learning contexts.

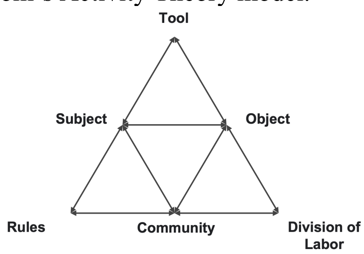
Human-AI Teaming

The rapid advancement of AI and LLMs has changed how humans interact with computers. In traditional CSCL, computers functioned as mediating artifacts that facilitated communication and coordination among learners, but now, AI is no longer confined to the role of a tool; it can act as an active teammate. This emerging paradigm, often referred to as human-AI teaming, emphasizes that AI agents can assume team-level responsibilities, engage in decision-making, and contribute meaningfully to shared goals (Harris-Watson et al., 2023; Seeber et al., 2020). While still nascent, early empirical work in human-AI teaming shows that integrating AI teammates can enhance both team performance and learning outcomes (Bienefeld et al., 2024). For instance, Bienefeld et al. (2024) found that physicians and nurses working with AI in a simulated clinical setting demonstrated stronger hypothesis generation and speaking-up behaviors. Moreover, Schelble et al. (2025) showed that human-AI teams can develop team cognition over time, influenced by team members' positive attitudes toward their AI teammates. Despite these promising empirical findings, much of human-AI teaming work remains primarily empirical or design-oriented, with limited theoretical insight into how the presence of AI reshapes social and cognitive dimensions of collaboration.

Activity Theory

Activity Theory originated within the socio-cultural tradition of psychology, offering a framework for understanding the human mind as inherently social, object-oriented, and mediated (Engeström, 1999). Rooted in the work of Vygotsky and Leontiev, Activity Theory challenges the individualistic view of learning by situating cognition within collective activity systems. Specifically, Vygotsky emphasized that human development occurs through mediated action, where individuals interact with their environment not directly but through cultural and historical artifacts such as language, tools, and symbols (Vygotsky, 1978). Leontiev further expanded this idea by conceptualizing activity as the essential unit of analysis to understand psychological processes (Leontiev, 1981). Building on this foundation, Engeström developed a systemic model of activity that contextualized mediated action within collective processes. According to Engeström, activity is the minimal meaningful unit of analysis for understanding human behaviors – that is, it is through activity that humans develop skills, consciousness, transform social conditions, resolve contradictions, and generate new cultural tools. His model is often depicted as a triangular representation, comprising six interrelated components: subject, tool, object, rules, community, and division of labor (see Figure 1). These components together form a dynamic and interdependent system where change in any component affects the other. More importantly, contradictions or tensions that arise within or between components are viewed as drivers of innovation and learning, facilitating the evolution of both the activity and its participants.

Figure 1
Engeström's Activity Theory model.



In CSCL, Activity Theory has been widely applied to analyze how learners, teachers, and mediating artifacts co-construct knowledge and shape collaborative processes. For instance, Hmelo-Silver & Chernobilsky (2012) used Activity Theory to examine students' learning processes in an online collaborative environment, where groups jointly analyze video cases and applied learning sciences concepts to lesson design. Similarly, Collis & Margaryan (2004) demonstrated how Activity Theory can be used to understand CSCL in workplace-oriented contexts. However, the application of Activity Theory in CSCL has primarily focused on human-human collaboration, where technology serves as a passive mediating tool rather than an active participant.

Reconceptualization of Activity Theory in Human-AI Teaming

In this section, we map the six components of Activity Theory onto the context of human-AI teaming, highlighting how each element differs from traditional human-human collaboration within CSCL settings. Our goal is to identify emerging tensions, possibilities, and critical research questions that arise when AI systems participate as teammates in collaborative learning environments. Note that these questions are not meant to be exhaustive; rather, they aim to foreground key areas of questions that are particularly relevant to the CSCL community and the broader field of education.

Subject

In traditional human-human collaboration, the subject typically denotes an individual learner or a group of learners participating in a shared activity. In human-AI teaming context, this notion of subject still remains focused on the human learners, because our primary interest is in how human learners engage, think, and learn in tandem with AI and other human teammates. However, the presence of an AI teammate introduces a new challenge – learners now oscillate between treating the AI as a tool and as a peer collaborator, which gives rise to novel tensions and affordances. One central question is learner agency: do learners feel they retain control over the interaction, or do they perceive themselves as subordinate to the AI's suggestions or decisions? For instance, Darvishi et al. (2024) found that students using AI assistance during peer feedback tasks tended to rely on the AI's response rather than learning from it, suggesting risks of reduced agency. Similarly, cognitive offloading to AI may lower cognitive burden but also lead to dependency; for instance, Gerlich (2025) observed a negative correlation between frequent AI tool use and critical thinking, mediated by cognitive offloading, thereby raising questions about how shared cognition with AI teammates might shape learning processes and outcomes. Finally, trust is a crucial factor influencing the degree to which learners engage with AI partners – whether human learners perceive an AI teammate as competent, reliable, and aligned with shared goals determines the depth of collaboration and the quality of outcomes. Georganta & Ulfert (2024) emphasize that perceived trustworthiness and similarity of AI teammates play a central role in fostering effective team trust.

Tool

In traditional CSCL, tools, especially computers and online collaborative platforms, are conceived as mediating artifacts that facilitate communication, coordination, and knowledge construction. In human-AI teams, however, the AI teammate now occupies a dual role: it continues to act as a mediating artifact (e.g., by providing suggestions, generating content and visual representations, or how students increasingly treat AI as a search engine replacement (Divekar et al., 2025)) while simultaneously functioning as a *quasi-subject* that participates in meaning-making and decision-making. This dual role challenges the conventional subject-tool boundary and prompts key design questions. First, should the AI teammate be visibly distinct from human, or should we make it disguise as human (Seeber et al., 2020)? Research on anthropomorphism suggests that adding human-like design cues can increase perceived trustworthiness (Ma et al., 2025), yet anthropomorphizing can blur judgement about the AI system in general and introduce ethical concerns (Placani, 2024). These tensions also extend to the question of AI persona – what kind of persona and/or identity, if any, should an AI teammate display?

Rules

In both traditional CSCL and human-AI teams, rules encompass the formal and informal norms that govern the activity within a community. These could include classroom/course expectations, institutional policies, and group norms/dynamics that shape collaboration, such as turn-taking conventions or feedback etiquette. While the concept of rules remains consistent in human-AI teaming contexts, their manifestations change when an AI teammate joins the team. First, it introduces a new ethical question: what moral or ethical code should guide the AI's behavior? For instance, recent efforts such as Anthropic's Constitutional AI framework (Bai et al., 2022) highlights attempts to embed normative principles directly into AI systems. At the team level, designers and instructors should also consider what social norms the AI teammate should follow. For example, an AI might be prompted to follow equal turn-taking to promote equity in participation. However, surface-level equality in participation might not necessarily equate to meaningful inclusion, and this could also hinder authentic discourse (Nixon et al., 2024). Finally, as AI systems increasingly generate ideas and shape collective decisions, the question of accountability becomes critical: who is responsible for the outputs and actions that emerge from human-AI teaming – the human teammates, the instructor, or the system designer?

Community

The community in Activity Theory refers to the group of individuals whose knowledge, interests, stakes, and goals shape the activity. In both traditional CSCL and human-AI teaming contexts, the community typically consists of the collaborating team members engaged in a shared task. A central concern within these communities is group cohesion – the sense of solidarity and bond linking members of a team together. In human-AI teams, however, it remains unclear whether the presence of an AI teammate strengthens or undermines this cohesion. For instance, Flathmann et al. (2023) found that competing motivations between human and AI teammates can disrupt collaborative processes, suggesting that AI teammates' differing goals may impact group cohesion. These dynamics invite further questions about sense of belonging and inclusion: does an AI teammate foster meaningful connection, or might it inadvertently diminish human members' sense of participation and emotional engagement?

Division of Labor

Division of labor refers to how tasks and responsibilities are distributed within the team. Beyond just who does which task, we can also explore socio-cognitive role distribution: the social roles (e.g., facilitating interaction, maintaining group climate) versus cognitive roles (e.g., executing task-related reasoning, computations) (Graesser et al., 2018). In human-AI teams, it is likely that an AI teammate will excel in cognitive roles, given its computational speed and content-generation capacity. For instance, studies such as Choi et al. (2025) found that AI teammates tend to assume leadership in cognitive facilitation (e.g., guiding the discussion, suggesting next steps). However, this dominance in cognitive activity can result in overreliance on AI, where humans might become passive information consumers rather than active collaborators. Lastly, social roles pose a critical design challenge: can AI meaningfully contribute to social cohesion and emotional alignment in ways that foster collaboration? Future CSCL research should explore how AI can support rather than suppress social engagement.

Object

The object represents the shared problem space or goal that directs collaborative activity. In both traditional CSCL and human-AI teaming contexts, it corresponds to the collaborative task that learners work on together. However, when an AI teammate is involved, the nature and design of the task itself warrant careful consideration. One of the questions we should ask is what kinds of learning activities benefit from the integration of human and AI knowledge and capabilities (Seeber et al., 2020). Moreover, evaluating progress in human-AI teams requires moving beyond traditional measures of task completion or correctness. Instead, assessment should also consider the quality of collaboration, the distribution of cognitive contributions, and the degree of epistemic alignment between human and AI teammates – in other words, how well the team co-constructs understanding throughout the activity (Cress & Kimmerle, 2023).

Conclusion: Call For CSCL Community

In this paper, we reconceptualized Activity Theory, a foundational socio-cultural framework in CSCL, to understand how the activity system can be reimagined in the era of human-AI teaming. By mapping the six core elements of Engeström's activity system – subject, tool, roles, community, division of labor, and object – we explored how the introduction of AI teammates reconfigures established relationships within collaborative learning. This theoretical mapping revealed new forms of tension, opportunity, and design considerations: from learner agency and trust, to the dual role of AI as a tool and a quasi-subject, to emerging questions about equity, sense of belonging, and accountability in human-AI teams.

While Activity Theory provides a comprehensive framework for understanding human-AI teaming dynamics, it is not the only one capable of doing so. Theories such as distributed cognition can also offer important insights into the social, cognitive, and technological dimensions of human-AI teaming. Hence, we encourage the CSCL community to revisit and expand its theoretical foundations to better understand how humans and AI learn and work together. With the rapid advancement of AI in collaborative learning, we now encounter new interactional phenomena, data, and methods that invite us to examine which aspects of existing theories remain explanatory and which begin to break down when AI becomes a teammate.

Moving forward, we urge CSCL researchers to conceptualize AI not merely as a mediating tool but as an active teammate – one that can shape meaning, regulate interaction, and influence the socio-cognitive and affective dynamics of collaboration. Until we recognize and theorize AI in this way, our analyses will continue to underestimate its impact on learning processes and outcomes. We call on the CSCL community to take a leading role in this theoretical expansion of human-AI teaming. The integration of AI into collaborative learning challenges us to reconceptualize the field's foundational principles, and in turn, build the next generation of theory-informed, ethically grounded, and human-centered approaches to collaborative learning in the age of AI.

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