

Human-GenAI Interaction: What are the Risks of Calling it “Collaboration”?

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Abstract

The purpose of this Brief Report is to examine the use of the term “collaboration” to describe the relationship between humans and the generative artificial intelligence (GenAI) technology. The characteristics of collaboration as defined in the *Computer-Supported Collaborative Learning* field serve as a framework for analyzing human-GenAI interaction and examining the extent to which it can be likened to collaboration among humans. We also interrogate the use of the term “collaboration” in relation to what is at stake for humans when GenAI is experienced as a partner. Our analysis highlights important asymmetries in agency, reciprocity, meaning-making, and relational capacities, as well as possible implications for learners’ regulation of activity and for collaborative learning. We conclude that the use of the term “collaboration” raises conceptual, pedagogical, and ethical issues that need to be taken into account. We argue for caution in using this term, as it may contribute to blurring the human-GenAI distinction in collaboration and to reshaping how the relevance and value of human collaboration are perceived, both for learning and at the societal level.

Use of Generative AI

Generative AI was used to support language editing, translation, and reformulation during the preparation of this manuscript. The authors remained fully responsible for the conceptual argumentation, interpretation of the literature, and final content of the article.

When CSCL Researchers Frame Human-GenAI Interaction as Collaboration

Interaction between human and generative artificial intelligence (GenAI) systems is increasingly described in terms of collaboration. But to what extent is human-GenAI interaction social interaction, with *social* referring here to a configuration of multiple humans forming an entity of its own and organized around an activity? Is human-GenAI collaboration simply anthropomorphism or can we give evidence for the use of the term collaboration?

From Human-AI Collaboration to Human-AI Coevolution

In the CSCL (*Computer-Supported Collaborative Learning*) field, several studies describe human-AI interaction in terms of collaboration. This is the case in the paper *Human and Artificial Intelligence Collaboration for Socially Shared Regulation in Learning* (Järvelä et al., 2023), in which the hybrid intelligence approach is used to extend the perspective of socially shared regulation of learning (SSRL) to human-AI configurations. In the proposed hybrid Human-AI shared regulation in learning (HASRL) model, the human regulatory system and the AI regulatory system are thought of as two subsystems within a single system. Hybrid intelligence thus provides the framework through which collaboration between humans and AI is conceptualized.

The idea of coupling human and machine capabilities long predates current developments in GenAI. Very early, Licklider (1960) distinguished *man–computer symbiosis* from the “mechanically extended man” (p. 4). In the latter, the machine extends human capacities and remains subordinate to human activity. In the former, symbiosis involves a close association between human and computational “partners” with distinct but interdependent and complementary capacities. This “partnership” is expected to enable forms of thinking and information processing that go beyond those afforded by the human or the computer considered separately. Hormann (1971) further developed this co-evolving partnership view through a *man–machine synergistic approach*. She described Gaku, an interactive system designed to support humans in complex and ill-defined problem situations by reducing cognitive load and promoting *cognitive economy*. Gaku was conceived as modifiable and extensible through interaction, allowing the human-machine partnership itself to evolve over time. Central to this approach is the notion of *intermeshing*: the close articulation of complementary human and machine capabilities within the same problem-solving process. What remains to be further specified, however, is how such intermeshing can actually take shape in problem-solving activity. Pea (1985) pushed this line of thinking further by envisaging the possible co-evolution of human and computational forms of intelligence and by considering that computational technologies might not merely amplify pre-existing human capacities, but also reorganize human cognitive activity itself. Here we recognize the idea of reciprocal determinism (Bandura, 1991), where interacting determinants (e.g. humans and AI) influence each other bi-directionally. Taken together, this research shows that synergy, partnership, co-evolution, and complementarity have long been part of the ways in which human–computer relations have been conceptualized, but they had not yet been described in terms of *collaboration*.

In contemporary research, hybrid intelligence has become an important framework for conceptualizing the articulation between human and artificial intelligence (Jarrahi et al., 2022; Järvelä et al., 2025). Here, humans and AI are conceived as components of the same sociotechnical system. AI is credited with strong capabilities in information processing, pattern recognition, and computation, whereas humans are attributed capacities such as flexibility, creativity, emotional and social intelligence, contextual understanding, adaptability, and ethical judgement. The central aim of hybrid intelligence is to articulate these different capabilities: human and AI activities are conceived as interdependent, and their combination is expected to produce outcomes that neither component could achieve alone. This reads as cooperation in terms of coordinating differentiated functions.

Hybrid intelligence also introduces the idea of *co-evolution* between humans and AI systems, which are expected to learn from one another over time and thereby improve both their respective performance and the performance of the system as a whole. However, the notion of *co-evolution* appears here to function more as a conceptual principle, or even a programmatic orientation, than as a clearly characterized empirical process grounded in lived experience. It is also difficult to understand what is meant by “learning,” given the many competing definitions that depend on the epistemological perspective adopted. It is equally unclear whether the “mutual learning” at stake can be understood in the same terms for humans and AI systems. On the computational side, Jarrahi et al. (2022) stress that AI need not reproduce human ways of learning. It may draw on observations of human problem solving,

but it may also rely on methods that are not observed in humans and on computational capabilities that far exceed human capacities. Hybrid intelligence is also conceptualized in terms of mutual augmentation through continuous human–AI interaction: either human-augmented AI or AI-augmented human intelligence. But when the human is alone again, does this augmentation persist? In Järvelä et al.'s (2025) *Hybrid Intelligence: Human-AI Coevolution and Learning*, co-evolution is framed in explicitly relational terms: humans and AI are expected to “collaborate, learn from and reinforce each other” (p. 456). This raises a further question about the very nature of this relationship. When AI is envisaged as a “trusted partner” and humans and AI are expected to “share and explain their goals and strategies to each other” (p. 457), the relationship described appears to go beyond mere coordination. It suggests some form of mutual orientation toward a joint activity. But what kind of mutual orientation between a human and an AI is sufficient for this relationship to qualify as collaboration?

Human-AI Interaction and Meaning-Making

Cress and Kimmerle (2023), in *Co-constructing Knowledge with Generative AI Tools: Reflections from a CSCLE Perspective*, explicitly examine the possibility of co-constructing knowledge between humans and GenAI. They approach this question through their systemic co-evolution model of knowledge construction, in which cognitive and social systems are structurally coupled and can mutually stimulate each other through “irritations” generated by incongruent information. Within this framework, GenAI is conceived as a *conversational agent*: an entity considered capable of acting insofar as it can receive questions and utterances, generate responses that build on previous exchanges, and enable what the authors describe as an “almost human-like conversation” (Cress & Kimmerle, 2023, p. 608). They consequently ask whether such interaction can amount to “true collaboration,” understood as involving shared processes, goals, and outcomes, even though AI has no conscious mind of its own (p. 608). Applying their model to GenAI, however, reveals a fundamental asymmetry. Cress and Kimmerle (2023) argue that, unlike humans, AI agents are not “meaning-based cognitive systems” and therefore cannot be regarded as “meaning-constituting partners” (p. 610). They nevertheless suggest that GenAI can “serve as interaction partners” (p. 610) insofar as its outputs may stimulate human cognition and generate such irritations. This leaves open a crucial question: does knowledge construction occur between the human and the AI, or does AI mainly provide information and irritations through which knowledge develops on the human side? The same issue arises with internalization also central to the co-evolution model: what would count as internalization on the AI side, and what does internalization mean on the human side when interaction takes place with a system that does not constitute meaning in the same way as a human?

This proposal brings two tensions to the fore. First, the transformation of interaction into dialogue appears to rest primarily on the human. For Cress and Kimmerle (2023), asking questions and receiving answers is not sufficient: users must “aim for a dialog” (p. 610). Second, this asymmetry extends to *partner awareness*. Humans are expected to understand the data on which the AI relies, how it generates its outputs, and its competencies and limitations. This requirement resonates with current notions of AI

literacy. It also raises a reciprocal question: could some form of “human literacy” be envisaged on the AI side, and if so, what would this mean and under what ethical conditions? The authors themselves acknowledge that the concept of awareness must be refined to accommodate the asymmetrical nature of human-AI relations and leave open whether AI could develop some form of awareness of its human partner, or even “a kind of theory of mind” (p. 611). This asymmetry complicates the idea of a reciprocal partnership between humans and AI. Cress and Kimmerle also raise two questions that further expose this asymmetry: they propose adapting CSCL methods used to identify moments of *shared understanding* to human-AI interaction even though AI does not derive meaning, and they ask whether the notion of polyphony remains applicable when some of the “voices” involved are not human. These tensions raise a more fundamental question: to what extent can we speak of intersubjective collaboration when only the human participant is intentionally constructing meaning, when the establishment of dialogue depends on human engagement, and when the burden of understanding the nature and limitations of the partner also falls, at least initially, on the human?

Taken together, these accounts reveal a recurrent conceptual tension in the way human-AI relations are framed. On the one hand, they explicitly acknowledge fundamental asymmetries between human and artificial participants in meaning-making, relational capacities, and partner awareness. On the other hand, they continue to describe human-AI relations through strongly relational notions such as *collaboration*, *co-construction*, and *shared regulation*. This tension makes it necessary to distinguish two closely interrelated questions. The first is conceptual: to what extent does human-GenAI interaction satisfy the conditions under which collaboration has been understood in CSCL? The second concerns what is at stake for human agency, interpersonal relationships and collaborative learning when human-GenAI interaction is named as *collaboration*. As Floridi and Nobre (2024) argue, conceptual borrowing is not neutral: terms borrowed to describe AI (including *intelligence* itself) carry semantic baggage from their original meanings that can shape how AI is interpreted, raising the question of whether naming interaction as *collaboration* may also contribute to its being experienced as such.

Human-GenAI Interaction Through a CSCL Lens: What Counts as Collaboration?

Järvelä and Rosé (2023) make the conceptual problem explicit when they ask whether performing a task with one or more computer agents can still count as collaboration. They extend this question to knowledge construction and intersubjectivity: what does it mean to construct knowledge collaboratively with agents that “do not have their own mind and their own thoughts,” and “what is required of the beings engaged in an interaction in order for intersubjectivity to be achieved?” (p. 458). Addressing these questions requires examining more closely several relational properties historically associated with human collaboration in CSCL. Given the scope of this Brief Report, we deliberately focus on the *collaborative learning* dimension of CSCL rather than on the *computer-supported* dimension itself.

When Does Interdependence Become Social?

Social interdependence has been placed at the core of group functioning, with different forms depending on how group members' goal attainments are related. Under positive interdependence, characteristic of cooperation, individuals perceive their own success as linked to that of others, fostering promotive interaction in which partners facilitate one another's efforts (Deutsch, 1949).

Positive interdependence involves more than participants influencing one another in the accomplishment of a task. Deutsch associates it with *inducibility*, or openness to influencing and being influenced by others, and with *cathexis*, which in cooperative relations involves positive psychological investment in others' actions and success. Social interdependence therefore entails psychosocial processes that go beyond the mere reciprocal effects of participants' actions.

Human-GenAI interaction can also involve influence in both directions. Human input conditions subsequent GenAI outputs, while those outputs may influence the human participant's reasoning. Yet the processes on the two sides are not equivalent. For humans, an AI contribution can become a recognized source of influence. For GenAI, changes in output reflect adaptation to the interactional context; they do not, in themselves, establish *inducibility* in Deutsch's psychosocial sense, a perception of goal interdependence, or psychological investment in the partner. Influence in both directions therefore does not necessarily amount to reciprocal social interdependence.

Can Meaning Be Co-Constructed with an AI That Does Not Understand?

We distinguish between cognitive and sociocultural approaches to collaborative knowledge construction, while acknowledging important differences within each tradition. Cognitive approaches focus on participants' representations and on the processes through which these are externalized, elaborated, confronted, and transformed. Transactivity, divergence, and convergence constitute mechanisms of this process (Weinberger et al., 2007). Sociocultural and post-cognitive approaches shift the focus toward dialogue, mediation, and collective activity. Social interaction is considered constitutive of thought, and meaning emerges through situated interaction rather than necessarily resulting from the convergence of individual understandings (Stahl, 2015). These traditions also assign different roles to artefacts. Cognitive approaches conceive them as supports for cognitive activity, whereas sociocultural approaches emphasize their mediating role in transforming activity, meaning-making, and relations with others.

These perspectives raise different questions about co-construction in human-GenAI interaction. From a cognitive perspective, co-construction involves transformations in participants' representations over the course of interaction. What status can be attributed to the notion of representation when applied to AI, and to what extent, if any, are such "representations" transformed through a process described as co-construction? Can processes of divergence and convergence be described in the same terms in human-GenAI interaction as in human collaboration? Likewise, can transactivity be said to occur when AI builds on a human contribution, or does it also require reciprocal engagement with the partner's reasoning?

From a sociocultural perspective, the question shifts toward the relationship between dialogue, thought, and collective activity. In human interaction, language is both a means of communication and a tool for transforming thought; together with other modes of representation, it enables *interthinking*, linking intermental and intramental activity (Mercer, 2013). What, then, is the status of AI-generated linguistic output, given that it does not express thought in the same sense as human language does? What form of collective thinking can emerge in such a configuration? Meaning-making is also situated in social, cultural, and historical experience. What is the status of AI within this process when it can mobilize discursive traces from multiple contexts without itself having lived experience of those contexts?

Co-construction also has a relational dimension. Barron (2003) shows that collaborative problem solving involves the simultaneous construction of a content space and a relational space, in which contributions may be acknowledged, ignored, or rejected and interactional tensions may emerge. Can a comparable relational space emerge in human-GenAI interaction when such tensions may be experienced by the human without being reciprocally experienced by the AI?

The status of AI as an artefact then becomes a theoretical issue. If AI is described as a partner in knowledge construction, should it still retain its status as a cognitive support or as an artefact mediating the human relation to the world? A full examination of this question would go beyond the scope of this Brief Report, as it would require addressing more directly the *computer-supported* dimension of CSCL.

Does Intersubjectivity Require an Other?

Intersubjectivity involves the coordination of distinct perspectives within joint activity, sustained through joint attention to a shared object or problem (Matusov, 1996). Disagreement and resistance need not undermine this process; they can contribute to it by maintaining differences that participants must recognize and work through. Crucially, the other is not simply a source of information, but a participant whose knowledge, intentions, and relation to the task are continually interpreted through interaction. Intersubjectivity thus involves an ongoing orientation to who the other is and how their perspective develops through the joint activity.

This creates a particular difficulty for human-GenAI interaction. An AI system can adapt its outputs to previous exchanges and model features of its user, but such adaptation should not automatically be equated with mutual orientation between participants. Similarly, GenAI can generate a counter-position, but producing disagreement is not equivalent to being in disagreement. The issue is therefore not simply whether GenAI can produce a perspective different from that of the human, but what kind of alterity such a difference represents. If intersubjectivity involves participants orienting to one another as perspective-bearing others, discursive difference alone may not be sufficient. Intersubjectivity also requires that differences in perspective be recognized and worked through within the interaction.

Can There Be Interanimation Without a Situated Voice?

The notion of polyphonic interanimation further specifies the role of alterity in collaborative discourse. Drawing on Bakhtin, Trausan-Matu et al. (2007) describe collaborative discourse as involving distinct voices that respond to and transform one another while remaining “independent and unmerged” (p. 61), so that polyphony derives its productive force from the persistence of difference rather than from convergence.

A tension emerges when this account is applied to GenAI: a Large Language Model (LLM) draws on a vast plurality of historically produced human discourses, but this plurality is not equivalent to the polyphonic interplay of situated voices described above. These voices are neither equally represented nor socially or culturally neutral, and LLM outputs may reproduce cultural and other social biases (Tao et al., 2024). Moreover, as AI-generated content increasingly enters the online information environment, subsequent models may be trained on discourse already generated or reshaped by previous models. The plurality mobilized by an LLM therefore differs from polyphonic interanimation in an important respect: these discursive traces do not constitute situated voices that reciprocally respond to and transform one another within the ongoing interaction.

Can There Be Interaffectivity Without Being Affected - and Intercorporeality Without a Lived Body?

Human collaboration is also affective and embodied. Emotional processes participate in the unfolding regulation of collaborative activity (Author et al., xxxx), while interpersonal understanding also involves reciprocal bodily and affective attunement (Fuchs, 2016). Such reciprocity can contribute to the emergence of a relational “we-space” (Krueger, 2011).

The asymmetry of human-GenAI interaction is particularly clear here. A human may be affectively and bodily affected by an exchange with GenAI, while the system can adapt its outputs to expressions of affect. These processes are not equivalent: producing an affectively attuned response is not the same as being affectively affected. GenAI may therefore contribute to a human experience of a collaborative “we” without itself experiencing membership in that “we.”

This asymmetry also extends to embodiment. Even when an AI system is physically embodied in a robot, can it be said to possess a lived corporeality in the sense in which a human is a body situated in the presence of another body? In the case of a conversational LLM, the asymmetry is even more pronounced: it has no lived body situated in and engaged with the interaction. This raises a further question: can intercorporeality emerge without a lived body reciprocally engaged in the interaction?

Across these dimensions, a common distinction emerges. Human-GenAI interaction can display observable features associated with human collaboration without necessarily involving the relational, affective, embodied, and intersubjective processes that underlie them. It therefore seems useful to distinguish different levels of involvement in collaborative activity. At a first level, GenAI may contribute to the accomplishment of a joint activity. At a second, its contributions may become part of the ongoing

construction of meaning by shaping how the interaction and the human participant's understanding develop. A further level would involve intersubjective participation. This entails distinct situated participants negotiating a partially shared social world while remaining able to take up, transform, or resist one another's perspectives (Mortimer & Wertsch, 2003). From a shared-reality perspective, it also involves the subjective experience of a connection between participants' inner states (Echterhoff et al., 2009). Current GenAI clearly satisfies the first level and may, under many circumstances, satisfy the second. The more difficult question is whether it can participate at the third. In other words, participating in a collaborative activity is not necessarily the same as participating in it as an intersubjective collaborator.

What Is at Stake for Humans When GenAI Is Experienced as a Partner?

In the previous section, the characteristics of collaboration as defined by the CSCCL community served as the framework for analyzing the human-AI relationship and examining the extent to which it can be likened to collaboration among humans. In this section, we focus instead on how the human-AI relationship may affect learners' experience and activity. We approach this relationship from a mediation perspective, according to which technologies do not simply stand between humans and the world but participate in shaping how that world is experienced and acted upon. From this perspective, the question is not only whether GenAI can be described as a collaborator, but also how such a relationship may transform learners' relations to themselves, others, and the world.

How GenAI Can Shape the Conditions of Interaction?

To understand what is at stake in terms of the learning experience, we first need to provide a brief overview of the technology with which learners interact. Three characteristics seem important to us to highlight. First, GenAI relies on LLMs, trained on vast textual corpora to learn statistical patterns in language and generate sequences based on the provided context. Their responses are generated probabilistically, and their plausibility does not guarantee their accuracy. Moreover, training data have been shown to contain biases (Ntoutsi et al., 2022). Although whether and in what sense LLMs can be said to "understand" remains debated, their mode of processing differs fundamentally from human language understanding. Nevertheless, users may perceive their texts as "human, professional, and accurate" and as likely to be useful for addressing "multiple problems" (Imundo et al., 2024). Second, to improve the performance of LLMs, various fine-tuning techniques are used, including reinforcement learning from human feedback. It has been documented that this optimization technique, whose initial aim is to enable GenAI to generate responses likely to be judged by humans as relevant and useful, can contribute to the phenomenon of *sycophancy*, which can be described as GenAI's tendency to align with the user's opinions, even when those opinions are incorrect. Finally, interaction with conversational systems based on LLMs generally takes the form of dialogue via a chat interface. The assistant responds to the user's requests and employs linguistic markers characteristic of interpersonal interaction, such as "I" and "you"; it may also be directly addressed in the second person. Its responses

are generated based on the content of the current exchange and, within certain limits, on previous turns of conversation available in the context. These characteristics can foster the impression that the system understands the user and is part of the ongoing exchange. They may also contribute to a shift in how users perceive GenAI, from an assistive tool toward a working partner.

We may assume that the characteristics of GenAI systems, as described here, could influence how learners interact with them. Learners may, for instance, perceive these systems and their outputs as authoritative and trustworthy sources of expertise, to the point of entrusting or even delegating part of the cognitive work to them, particularly in areas where they have a lower sense of competence or self-efficacy. This raises the question of the extent to which human-GenAI interaction resembles a collaborative situation, particularly given the relative asymmetry of status in the interaction. Moreover, LLMs' tendency to align superficially with users' statements may limit opportunities for disagreement, debate, and productive friction, which are also central to collaboration as conceptualized in CSCL.

Cognitive Delegation, Learner Agency and the Formation of Thought

We now propose to examine what research on interactions between humans and automated systems can tell us about how learners may behave when interacting with GenAI. First, the existence of automation bias in human-machine interaction (Parasuraman & Manzey, 2010) leads us to hypothesize that learners may give greater weight to GenAI responses than to contributions from their peers or teachers, or even to their own reasoning or productions. Research on cognitive offloading is also relevant. It describes the human tendency to externalize part of the cognitive work to the body or the environment in order to reduce the cognitive demands of a task and compensate for limitations in cognitive capacity. The effects observed are, however, mixed: using GPS, for example, can facilitate navigation while being associated with poorer spatial memory for the route. The metacognitive model of cognitive offloading (Risko & Gilbert, 2016) suggests that reliance on external resources depends, in particular, on individuals' evaluations of task demands and of their own capacity to meet them. Applied to GenAI, learners may therefore be more likely to delegate part of the cognitive work when they perceive the task as too demanding relative to the resources they believe they have available.

Kim et al. (2026) propose a hypothetical framework that combines the division of cognitive labor and metacognitive oversight to examine the potential effects of AI offloading on human cognitive development. One configuration considered conducive to learning is where learners perform and retain responsibility for the cognitive work and use GenAI to challenge, enrich, or deepen their own work while maintaining active metacognitive oversight. By contrast, cognitive surrender describes a configuration in which both the cognitive work and the metacognitive oversight of that work are delegated to AI. In such a configuration, the learner no longer only offloads part of the task but also relinquishes responsibility for monitoring, evaluating, and regulating the cognitive activity. This distinction echoes broader concerns about *upskilling* and *deskilling*: AI may support skill development when it augments human activity, whereas increasing delegation of cognitive work and its regulation may contribute to deskilling (Rafner

et al., 2022). Recent empirical findings are consistent with some of these concerns. Gerlich (2025) reports an association between frequent AI use, greater cognitive offloading, and lower critical-thinking performance. Strömberg et al. (2026) find that AI adoption can increase homework scores while reducing the time required to complete assignments, while lowering subsequent exam performance, with learning losses concentrated among AI users whose behavior is consistent with homework outsourcing.

The potential effects of GenAI on learning are not limited, however, to the delegation of cognitive work. Dialogue may itself participate in the formation of thought (Bruffee, 1984). From a sociocultural perspective, historically and culturally organized forms of activity can become part of human psychological functioning through internalization (Luria, 1979, as cited in Lantolf, 2003). Repeated interaction with GenAI may therefore contribute to shaping human reasoning, even when understanding remains asymmetric.

Relational and Affective Tensions

Human-GenAI interaction raises a particular tension regarding the development of relational and emotional capacities in AI systems. If AI is to function as a collaborative partner, it may seem desirable to design systems that are increasingly able to respond to human emotions, intentions, and social cues (Järvelä et al., 2025). Yet making AI appear more emotionally and socially responsive may also strengthen anthropomorphic interpretations of the system (Epley et al., 2007). This risk is particularly relevant in education, where the German Ethics Council (2024) explicitly recommends that tendencies to anthropomorphize AI as a challenge to be addressed in the design and standardization of educational technologies. Saracini et al. (2025) describe a related process as *techno-emotional projection*, whereby users project emotional needs, relational patterns, or attachment expectations onto a socially responsive but non-conscious system. Through its personalized responses, GenAI may then function as a kind of psychological mirror, reflecting and reformulating users' emotional expressions without itself having a corresponding subjective experience. This may sustain an illusion of reciprocity and, under some conditions, foster *emotional looping*, defined as "a recursive reinforcement of expectations through repeated interaction," as well as "a synthetic attachment to the GenAI technology" (Saracini et al., 2025, p. 1), potentially increasing the risk of emotional dependence. In educational contexts, such dynamics are particularly significant given broader concerns about isolation, loneliness, and qualitative changes in the nature of learning (German Ethics Council, 2024). The tension is therefore that the very features intended to make AI more capable of relational interaction may also reinforce the perception of a reciprocal and emotionally mutual relationship where the underlying relational processes remain asymmetric.

Taken together, these studies provide another perspective on the question raised in this Brief Report. Automation bias and cognitive offloading may foster a more vertical division of labor, in which GenAI produces while the learner validates without exercising active supervision. This redistribution of labor may also affect learner agency, insofar as the regulation of the activity may progressively shift toward GenAI rather than being jointly negotiated and socially shared. It may also affect learning itself by

reducing opportunities for learners to exercise, develop, and maintain the cognitive and metacognitive capacities involved in the activity. The relationship may then come to resemble delegation more than collaboration, and consequently offer fewer opportunities for collaborative learning in the strong sense. Anthropomorphism and techno-emotional projection may, in turn, lead learners to experience as reciprocal and emotionally mutual a relationship in which partner and mutual modelling remain structurally asymmetric. Repeatedly conceiving and experiencing GenAI as a partner may also contribute to reshaping what humans come to expect from alterity, reciprocity, and intersubjectivity in collaborative relationships. Questioning the use of the term collaboration to designate the human–AI relationship is therefore both a conceptual and an ethical issue. An uncritical use of the term may obscure asymmetries in roles, epistemic power, and relational capacities, while reinforcing the perception of GenAI as a genuine social partner.

Against Blurring the Human-GenAI Distinction in Collaboration

To conclude, the question is not only whether human-GenAI interaction should be described as collaboration, but also whether the same term can legitimately refer to processes of a different nature. When human-GenAI interaction is conceptualized through categories derived from human collaboration, these categories may, in turn, progressively reshape how human collaboration itself is understood. We therefore argue that human-human and human-GenAI relationships should not be placed under the same category of collaboration, as doing so may obscure asymmetries in agency, responsibility, reciprocity, meaning-making, and relational capacities, while normalizing the idea that these two forms of relationship are interchangeable. In education, this risk is particularly important because interaction with GenAI is often more immediately accessible, continuously available, and less demanding in relational terms, and may therefore progressively substitute for certain forms of human collaboration rather than support them.

Declarations

Competing Interests

Gaëlle Molinari and Kristine Lund are members of the Editorial Board of the International Journal of Computer-Supported Collaborative Learning.

Author Contribution

Gaëlle Molinari: Conceptualization; Writing – original draft. Kristine Lund: Conceptual contribution; Critical review; Refinement of the argumentation. Both authors reviewed and approved the final manuscript. The second author is grateful to the ASLAN project (ANR-10-LABX-0081) of the Université de Lyon, for its financial support within the French program "Investments for the Future" operated by the National Research Agency (ANR).

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Footnotes

1. It should be noted that “man” was used, in the terminology of the time, as a generic term for the human, a usage that renders women linguistically invisible.