Exploring the Design of GenAI-Based Systems to Support Socially Shared Metacognition

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Abstract

Socially shared metacognition (SSM) refers to the collective monitoring and regulation of joint cognitive processes in collaborative problem-solving, and is essential for effective knowledge work and learning. Generative AI (GenAI)-based systems offer new opportunities to support SSM, but emerging evidence suggests that poorly designed systems can encourage over-reliance on AI-generated explicit instruction and erode groups' capacity to develop autonomous regulatory processes. Group awareness tools (GATs) address this challenge through established design principles that make social and cognitive awareness information visible, highlight differences between group members to create cognitive conflict, and trigger autonomous elaboration and discussion, thereby implicitly guiding autonomous SSM emergence. This paper explores the design of GenAI-augmented GATs to support autonomous SSM in collaborative work and learning through an initial literature search, presenting preliminary design principles for discussion.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**; • **Computing methodologies → Artificial intelligence**.

Keywords

generative AI, GenAI, large language models, LLMs, artificial intelligence, AI, cognition, metacognition, socially shared metacognition, SSM, co-regulation, self-regulation, autonomy, autonomous regulatory processes, explicit instruction, implicit guidance, group awareness, group awareness tools, GATs, computer-supported collaborative learning, CSCL, collaborative problem-solving, knowledge work, interaction design, user interface design, visualization

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1 Introduction

Collaboration in modern knowledge work and learning environments has become increasingly complex. Team members may need to navigate distributed communication platforms, reconcile diverse disciplinary perspectives, synthesize information scattered across multiple sources, coordinate asynchronously across locations, and continuously adapt to evolving circumstances [1, 43]. Given these demands, the ability to collaborate effectively has become fundamental for both workers and learners [29, 37].

Central to effective collaboration is socially shared metacognition (SSM), where group members collectively monitor and regulate their joint cognitive processes in collaborative problem-solving [20, 23]. Rather than each person independently tracking their own understanding, the entire group works together to assess collective knowledge, identify gaps, plan approaches, monitor progress, and adjust strategies, among other activities [18, 19]. When groups engage in SSM, they may achieve stronger decision-making, more effective problem-solving, and deeper shared knowledge construction, among other benefits [24, 34, 48].

Yet SSM rarely emerges spontaneously [46, 47], creating needs for intervention [38, 42]. Thanks to their understanding and generative capacity [22, 53–57], GenAI-based systems present new possibilities for supporting SSM through, for example, automated monitoring of group processes and timely feedback provision [17, 44]. However, poorly designed GenAI-based systems may encourage over-reliance on AI-generated explicit instruction and erode groups' capacity to develop autonomous regulatory processes [2, 33, 36, 50].

GATs address this challenge through established design principles that make social and cognitive awareness information visible, highlight differences between group members to potentially create cognitive conflict, and may trigger autonomous elaboration and discussion, thereby implicitly guiding autonomous SSM emergence [40, 41]. GATs externalize information about group functioning through visualizations such as participation patterns, knowledge distributions, and progress indicators [30, 35]. While GATs interpret collaboration data to generate awareness information, they present this as observable patterns for groups to examine rather than prescriptive actions to follow [13, 40], potentially preserving groups' autonomy over monitoring, evaluation, and planning activities [39].

This paper explores the design of GenAI-augmented GATs to support autonomous SSM in collaborative work and learning contexts. Through an initial literature search of existing GAT systems, we address three research questions:

- **RQ1:** What group awareness information can GenAI generate?
- **RQ2:** How can user interfaces present GenAI-generated group awareness information?
- **RQ3:** How can interaction techniques enable exploration of GenAI-generated group awareness information?

Our contribution addresses the workshop's "TfT Strategies: Design and Usage" theme by offering preliminary design principles for GenAI-based systems that protect human cognitive processes while leveraging AI capabilities where they add value.

2 Background and Related Work

SSM encompasses three regulatory processes through which groups collectively control their collaborative work [24, 25]. In shared planning, groups jointly determine task approaches, role distributions, and resource allocation, among other activities [18]. During shared monitoring, groups track ongoing progress, contribution patterns, and emerging outcomes [3]. Through shared evaluation, groups assess results and processes against criteria such as initial goals and quality standards [3, 18]. These processes may operate cyclically: evaluation insights can inform subsequent planning, which shapes what groups monitor, leading to further evaluation.

Supporting these regulatory processes requires groups to develop group awareness, understood as knowledge of their collective state including how the collaboration functions and how knowledge distributes among members [5, 15, 28]. Group awareness may encompass cognitive dimensions (e.g., what members know and understand about tasks) and social dimensions (e.g., how members participate and interact) [4, 26, 27].

GATs support SSM by externalizing group awareness information through visual representations [30, 35]. For example, cognitive GATs may display comprehension levels through bar charts or knowledge structures through concept maps [14, 40]. Social GATs may visualize participation patterns through contribution counts or interaction quality through discourse analysis [27, 32]. Critically, GATs employ a distinct support mechanism: rather than providing explicit instruction on what groups should do, they present awareness information as observable patterns that groups interpret themselves [13, 40], potentially creating cognitive conflict through visible discrepancies such as uneven participation, knowledge gaps, or performance shortfalls, which may trigger autonomous elaboration and discussion [34, 40]. This approach has the potential to preserve monitoring, evaluation, and planning within group control rather than delegating these regulatory processes to the system [39].

GenAI introduces new possibilities for augmenting GATs [9, 10]. Traditional GATs typically display raw data or simple visualizations derived from structured collaboration data [7, 52]. GenAI may analyze unstructured collaboration artifacts such as discussion transcripts or document revisions [6, 45], potentially enabling richer awareness information about nuanced collaboration aspects, such as whether members build on each other's ideas, who demonstrates deeper understanding, or which misconceptions are developing [21, 45]. However, integrating GenAI while preserving GATs' core principle of implicit guidance rather than explicit instruction requires careful design consideration.

3 Methodology

To develop preliminary design principles for GenAI-augmented GATs, we conducted an initial literature search of existing GAT systems that support SSM in collaborative contexts. We searched three digital libraries, including ACM Digital Library, IEEE Xplore, and Scopus, using search terms combining concepts such as "group awareness tools", "socially shared metacognition", "shared regulation", "collaborative metacognition", and "awareness visualizations", among others. We did not include explicit terms for GenAI, since all GATs, whether GenAI-based or not, may serve as potential sources for informing GenAI-augmented system design.

We applied lightweight inclusion and exclusion criteria suited to the exploratory scope of this workshop paper. We included peer-reviewed papers describing systems with UI designs or interaction techniques for group awareness externalization that discuss their role in facilitating SSM or related constructs. We excluded secondary studies, purely theoretical papers, and systems relying on non-traditional modalities such as augmented or virtual reality, as these warrant separate investigation. To complement the initial database search, we conducted a round of backward snowballing on included papers to identify additional relevant systems that might otherwise have been missed.

The resulting set of papers was analyzed thematically to identify patterns in how GATs generate, present, and support exploration of group awareness information. These patterns informed the three preliminary design principles discussed in Section 4. We acknowledge that this initial search is not exhaustive, and a more rigorous systematic review would be needed to validate and refine these principles in future work.

4 Initial Findings

4.1 Generating Group Awareness Information

GenAI's distinguishing capability may lie in interpreting unstructured collaboration content. Traditional GATs typically employ rule-based approaches that apply predefined logic to structured data [4, 26], and may excel at tasks such as counting message frequencies, calculating participation ratios, or aggregating self-reported understanding levels. However, they may struggle with awareness information requiring interpretation of unstructured content, such as assessing whether members demonstrate shared understanding, identifying reasoning quality in discussions, or detecting emerging conflicts from language cues [6].

GenAI may analyze unstructured collaboration artifacts such as discussion transcripts, document revisions, or annotations to infer cognitive and social states that resist formalization into explicit rules [6, 45]. For example, rather than merely counting contributions, GenAI might examine what members wrote to assess whether explanations demonstrate conceptual understanding, or whether members build on versus talk past each other.

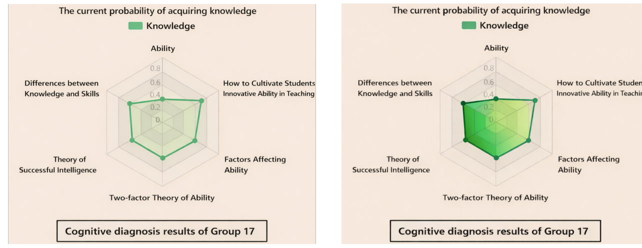
However, GenAI's value may vary substantially across awareness information types. For awareness information requiring semantic understanding of unstructured content, GenAI may offer clear advantages, such as inferring collaboratively defined norms, shared understanding, communication quality, or reasoning processes. For awareness information derivable through straightforward computation of structured data, traditional approaches may remain more suitable, including individual contribution quantities, participation patterns over time, and activity completion status [7, 52]. Between these extremes lies awareness information that could potentially benefit from GenAI's semantic capabilities but may also be adequately generated traditionally, depending on available data structures. For example, quality of collaborative processes could be analyzed through GenAI discourse analysis or assessed through predefined rubrics; comprehension development could be tracked through GenAI analysis of evolving contributions or through periodic structured assessments; and participation distribution could potentially benefit from GenAI's ability to distinguish substantive from superficial contributions, though basic quantitative metrics may remain useful for identifying gross imbalances.

> **Design Principle 1:** *Employ hybrid architectures combining rule-based systems for quantitative metrics requiring computational precision with GenAI for qualitative assessments requiring semantic understanding of unstructured collaboration content.*

4.2 Presenting Awareness Information

A critical challenge emerges when presenting GenAI-generated awareness information: groups may perceive GenAI's semantic assessments as definitive judgments rather than provisional interpretations [2, 49], potentially undermining SSM by discouraging independent critical evaluation. We propose a core design strategy: GenAI-generated semantic interpretations should appear as *secondary* visual encodings that augment rather than replace quantitative representations. By encoding GenAI assessments through visual properties such as color saturation, background shading, or overlay indicators, while preserving traditional quantitative metrics as primary visual channels, groups can perceive both objective quantities (what occurred) and semantic qualities (what it might mean) simultaneously [12, 31, 58]. Critically, this dual encoding may create cognitive conflict: when groups observe discrepancies between their primary quantitative view and the secondary GenAI-generated interpretation, this psychological discomfort may trigger autonomous elaboration and discussion, prompting groups to interrogate the difference rather than passively accept either representation.

Consider radar charts showing knowledge levels across domains (Figure 1) [59]. Rather than mapping GenAI analysis directly onto the shape of the polygon, which would position AI assessment as the sole source of information, a GenAI-augmented design might maintain the polygon representing group self-reported understanding while showing GenAI's independent analysis of actual discussions through background color intensity on axis segments. Darker backgrounds may indicate alignment between what groups reported and what they demonstrated in discussions, while lighter backgrounds may indicate differences. This juxtaposition may create cognitive conflict: groups observing a light background on an axis where



(a) Without GenAI integration (reproduced from [59], translated into English with minor visual revisions).

(b) With GenAI integration.

Figure 1: Comparison of radar and spider chart UIs without and with GenAI integration.

they reported high understanding may be prompted to question their self-assessment, examine whether their discussions genuinely reflected that understanding, and decide whether additional work is needed or whether the GenAI analysis missed important context. Rather than instructing groups on what to do, this design implicitly guides autonomous monitoring and evaluation by making the tension between self-perception and demonstrated performance visible and open to group interpretation.

> **Design Principle 2:** *Present GenAI-generated semantic interpretations as secondary visual encodings such as color saturation, background intensity, or overlay indicators, that augment primary quantitative representations, creating cognitive conflict through visible discrepancies that may trigger autonomous elaboration and discussion while preserving groups' interpretive autonomy.*

4.3 Enabling Exploration Through Interaction

Beyond generating and presenting awareness information, GATs may provide interaction techniques enabling groups to explore visualized information. Such exploration may contribute to autonomous SSM by enabling groups to verify, question, and critically evaluate AI interpretations rather than passively accepting them, particularly when groups observe discrepancies between GenAI's visualized interpretations and their own experience.

Hover-for-details interactions involve moving the cursor over visual elements to reveal pop-ups [11, 21]. Applied to radar charts (Figure 2), when groups observe axes with light background intensity indicating differences between self-reported and AI-assessed understanding, hovering over those axes might trigger pop-ups displaying several layers of information. For example, the pop-up might show GenAI's assessed understanding level for that specific knowledge domain, making explicit what the background color intensity represents. It may also display a confidence score indicating how certain GenAI is about its assessment, potentially helping groups calibrate their trust in the interpretation. Additionally, it might present example discussion quotes that GenAI identified as evidence for its assessment, allowing groups to examine the actual

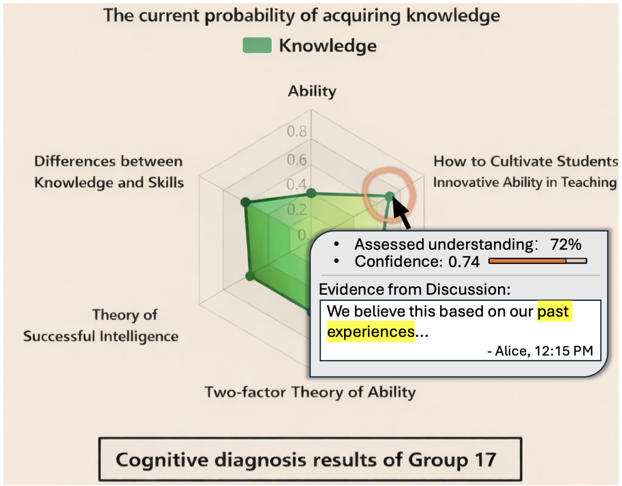


Figure 2: Hover-for-details interaction with radar charts.

statements that informed the AI's judgment. Together, this multi-layered information may enable groups to investigate why GenAI assessed understanding differently than the group self-reported, revealing both the system's reasoning and its uncertainty. Groups might then verify whether the quoted evidence aligns with their own interpretation, and decide whether the AI assessment warrants revising their self-perception or whether important context was missed.

Additional interaction techniques may further support exploration. Click-to-access interactions involve clicking visual elements to reveal underlying evidence [8, 21, 51], such as opening panels showing full discussion excerpts with highlighting that matches quality assessments. Selection and highlighting interactions involve clicking items to mark them for comparison [16], such as selecting multiple group members to view side-by-side statistics and example contributions with quality indicators. Together, these interaction techniques may help transform cognitive conflict created by the dual visual encoding into productive autonomous regulatory activity, as groups move from noticing discrepancies to actively investigating, evaluating, and deciding how to respond.

Design Principle 3: *Provide interaction techniques such as click-to-access underlying evidence, hover-for-details on assessments, and selection for comparison, that enable groups to investigate evidence underlying AI interpretations, compare AI assessments with their own experiences, and critically evaluate whether assessments are valid before deciding whether to act on them.*

5 Discussion

The design principles proposed in this paper operationalize GenAI as a tool for thought that protects rather than erodes autonomous regulatory processes in collaborative work and learning. By presenting AI-generated interpretations as secondary visual encodings that augment quantitative representations, these designs avoid positioning GenAI as an authoritative evaluator. Instead, GenAI may perform pattern detection that groups would struggle to accomplish manually with large volumes of unstructured collaboration data, while preserving regulatory decisions such as what patterns mean, whether they indicate problems, and how to respond, under group control.

The proposed principles may transfer across educational and workplace contexts because they address fundamental aspects of how groups develop awareness and engage in regulatory processes rather than domain-specific task characteristics. While most existing GAT research originates from educational settings [18, 30], workplace collaborations involving distributed expertise and collective decision-making may equally require effective SSM, though contextual adaptations are likely needed.

Additionally, a critical assumption underlying these principles is that groups will engage productively with GenAI-generated awareness information rather than finding it distracting or overwhelming during active collaboration. Several design considerations may help mitigate these risks. Awareness information might be surfaced at natural transition points rather than updating continuously during active task work. Progressive disclosure may also help: systems might initially surface only primary quantitative representations, with secondary GenAI encodings revealed on demand through interaction techniques. Finally, the salience of secondary visual encodings may need careful calibration, as encodings that are too prominent may disrupt task attention while encodings that are too subtle may fail to trigger cognitive conflict. These considerations suggest a direction for future design exploration.

6 Limitations

The proposed principles represent conceptually derived guidelines grounded in existing GAT patterns but lack empirical validation regarding their effectiveness in supporting autonomous SSM, their potential to create cognitive overload, or their capacity to engage groups productively in real collaborative settings. Future work should validate these principles through controlled studies and field deployments across diverse contexts.

7 Conclusion

This paper explored how GenAI-augmented GATs might support autonomous SSM in collaborative work and learning contexts. We proposed three preliminary design principles: employing hybrid architectures that deploy GenAI selectively for qualitative awareness information generation; presenting GenAI-generated awareness information as secondary visual encodings that may create cognitive conflict to trigger autonomous elaboration and discussion; and providing interaction techniques enabling groups to critically explore and evaluate AI interpretations. Together, these principles operationalize GenAI as a tool for thought that may augment rather than replace human cognitive processes, supporting implicit guidance rather than explicit instruction, thereby preserving rather than eroding groups' autonomous regulatory processes. Realizing this potential, however, requires careful attention to when and how awareness information is surfaced to engage rather than distract or overwhelm groups during active collaboration.

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