When Groups Struggle: A Framework of Trigger Events and Regulatory Breakdown in Socially Shared Regulation of Learning for Proactive AI Intervention

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Abstract

Collaborative work and learning share a common challenge: groups must coordinate cognition, motivation, and emotion toward shared goals, and this coordination frequently breaks down. In collaborative learning research, trigger events are theorised as markers and catalysts for regulatory response that arise when groups encounter difficulty. However, groups often fail to respond to them effectively, and what group-level regulatory breakdowns trigger events may produce and when AI might intervene remains underexplored. Drawing on Socially Shared Regulation of Learning (SSRL), a well-established framework in learning research, this paper proposes a framework that builds on existing trigger event categories to identify three categories of group-level regulatory breakdown that trigger events may produce, each with observable discourse signals. By distinguishing trigger event categories from the regulatory breakdowns they produce, the framework supports more targeted decisions about when and how proactive AI systems should intervene in collaborative learning.

Keywords

Proactive AI, Trigger Events, SSRL, Collaborative Learning, Intervention Timing

1. Introduction

The ability to collaborate across disciplines and sectors has become a defining competency of the twenty-first century, as networked forms of work and learning place increasing demands on groups [1, 2, 3]. In both collaborative work and learning, group members need to align their cognition, motivation, and emotion toward shared goals [4, 2], and this alignment frequently breaks down. Groups might encounter cognitive difficulties in establishing shared understanding, motivational tensions arising from differences in goals and commitment, and socio-emotional challenges that erode trust and engagement [1, 5, 6]. Such challenges are not incidental: they are a recurring feature of collaborative contexts across both educational and professional settings, and their effects on group processes can be substantial[7, 8].

What makes these moments significant is their role within Socially Shared Regulation of Learning (SSRL), an established framework in learning research. In SSRL, trigger events are theorised as markers and catalysts for regulatory response that arise when groups encounter difficulty during collaboration [9]. Rather than mere disruptions, trigger events mark the junctures at which groups have the opportunity to negotiate shared task perceptions, revise goals and strategies, and monitor their collective progress [4]. Collective regulation refers to the shared processes through which groups monitor and adapt their joint activity in response to these events.

Yet the conditions for collective regulation to emerge are not automatically met. Groups frequently fail to perceive trigger events as demands for regulatory action. High-performing groups tend to engage in regulatory processes in response to trigger events, whereas low-performing groups respond with routine-level strategies that leave deeper cognitive, metacognitive, and socio-emotional difficulties unaddressed [7]. When members hold divergent understandings of what the group is struggling with, regulatory responses become misaligned and the trigger event goes unresolved[6, 7].

Proceedings of TimelyAI: When Should Generative AI Assistants Intervene? A Workshop Co-located with the 5th Symposium on Human-Computer Interaction for Work (CHIWORK 2026), Linz, Austria, June 22 to 25, 2026
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CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073
published 2026-09-14

This recognition gap points to a potential role for proactive AI systems. The question of when AI systems should intervene in collaborative work has emerged as a central design challenge in recent HCI research [10]. The HASRL model positions AI as a regulatory subsystem alongside human learners, detecting trigger events from group signals, diagnosing the group's current regulatory state, and acting to scaffold rather than replace human regulatory agency [11]. Early empirical work lends initial support to this vision: NLP approaches can identify trigger event categories from collaborative discourse with reasonable reliability [12], and AI can serve as an extension of human cognition by making learning processes more visible and supporting self-aware regulation [13].

A theoretical gap remains, however. Existing approaches to trigger detection focus on classifying the content of trigger events, identifying whether groups are experiencing a cognitive, metacognitive, emotional, or socioemotional difficulty [14, 12]. This content-level classification is a useful first step, but it does not specify what has gone wrong in the group's shared regulatory processes. Two groups may both be experiencing a cognitive trigger event, yet one may have lost a shared understanding of what the task requires, while the other has stopped monitoring whether their strategies are working [4]. These are distinct regulatory failures that may call for different forms of AI support at different moments.

We propose a framework grounded in SSRL research that builds on the five trigger event categories established by Järvelä and Hadwin[9]. The central contribution is a second component that distinguishes three categories of group-level regulatory breakdown that trigger events may produce, namely shared task perception breakdown, metacognitive monitoring breakdown, and motivational-socioemotional breakdown, each with observable discourse signals that could inform the timing and nature of proactive AI intervention. Together, these two components support diagnosis of what kind of regulatory breakdown has occurred, enabling AI systems to determine more precisely when and how to intervene.

This paper raises two research questions:

- **RQ1:** What categories of group-level regulatory breakdown do trigger events produce in collaborative learning?
- **RQ2:** How can observable discourse signals associated with each breakdown category inform the timing of proactive AI intervention?

2. Related Work

2.1. Socially Shared Regulation of Learning

Socially Shared Regulation of Learning (SSRL) refers to the collective processes through which groups negotiate shared task perceptions, goals, plans, and strategies, and coordinate their cognition, motivation, emotion, and behaviour toward shared learning goals [4, 15]. Hadwin et al. [4] conceptualised SSRL as unfolding in four loosely sequenced phases: groups negotiate shared task perceptions, set shared goals and plans, coordinate strategy execution and monitor progress, and evaluate and adapt their collective approach.

SSRL is distinct from Self-Regulated Learning (SRL), which concerns individual regulatory processes, and co-regulation (CoRL), which involves one participant regulating another. SSRL involves the group as a whole exercising metacognitive control over their joint activity, a form of regulation that is qualitatively different from and more demanding than individual or dyadic regulation [15, 7].

Evidence suggests that SSRL is positively associated with learning outcomes, with high-performing groups exhibiting greater temporal variety in their regulatory strategies and more adaptive responses to challenges over time [1, 7]. Low-performing groups tend to deploy surface-level or routine strategies focused on time management and environmental factors, while showing less engagement with deeper cognitive, metacognitive, or socio-emotional challenges that call for collective attention [7].

2.2. The HASRL Model

Järvelä et al. [11] proposed the Human-AI Shared Regulation of Learning (HASRL) model (see Figure 1) to operationalise how AI and human regulatory systems can function as two interdependent subsystems within a hybrid intelligent system. The model builds on a trigger concept framework, in which internal and external trigger sources generate signals and traces that AI can detect and diagnose. Drawing on Molenaar's [16] detect-diagnose-act framework as the basic functioning of AI in education, HASRL positions AI as performing three core regulatory functions: detecting trigger events from group signals, diagnosing the group's current regulatory state through traces such as sequences and patterns, and acting to provide support that scaffolds rather than replaces human regulatory agency. Critically, the model also incorporates a learning component, in which AI systems adjust their models over time to better scaffold human regulatory competencies rather than simply automating responses. As Järvelä et al. [11] articulate, the goal is for AI to work with learners to facilitate SSRL by detecting challenges, sense-making, and recommending actions in real time. Recent work has explored GenAI-based systems designed to support shared metacognition in collaborative settings [17], suggesting that AI support for SSRL is technically feasible.

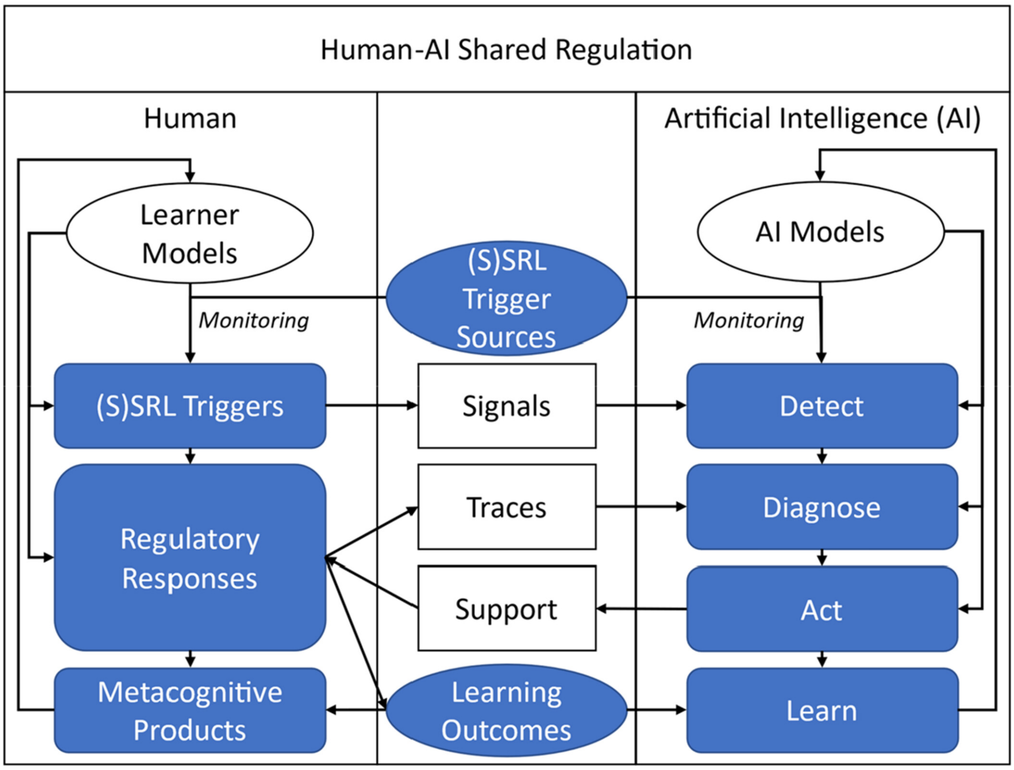

Figure 1: HASRL model adapted from Järvelä et al. [11]

2.3. Trigger Events in Collaborative Learning: Theory and Detection

Trigger events are defined as markers or catalysts for strategic regulation or the adaptation of motivational, cognitive, emotional, or behavioural regulatory approaches to optimise task progress[9]. They arise when groups encounter conditions that impede collaborative progress, including cognitive difficulties, motivational tensions, socioemotional conflicts, and behavioural disengagement[14, 9]. Järvelä and Hadwin[9] propose five categories of trigger events: motivational triggers, which occur when group confidence or task commitment falls below a functional threshold; cognitive triggers, which arise from difficulties in applying or connecting ideas; metacognitive triggers, which occur when groups struggle to interpret tasks or monitor their own progress; socioemotional triggers, which emerge when interpersonal dynamics or affective states become disruptive; and behavioural triggers, which occur when task engagement wanes. These categories are not mutually exclusive: a motivational trigger may cascade into a behavioural one, and a single situation can carry both cognitive and socioemotional dimensions simultaneously[9, 18].

Critically, trigger events can only invite regulatory action when they are perceived and interpreted as demands for response by the group [9]. High-performing groups demonstrate temporal variety in both the trigger events they identify and the strategies they deploy in response, whereas low-performing groups largely fail to activate regulation not because they lack regulatory repertoires, but because they do not recognise the situation as requiring one [7]. The qualitative characteristics of deliberative interaction following trigger events, not the frequency of regulatory behaviour, distinguish adaptive from maladaptive groups: adaptive groups respond to trigger events with a balanced interplay of cognitive, metacognitive, and task execution interactions, while maladaptive groups engage in reactive metacognitive activity without strategic planning, becoming trapped in repetitive cycles in which trigger events recur without producing qualitatively different responses[19, 20].

Recent work has begun to operationalise this insight in AI systems. NLP approaches applied to collaborative discourse can classify trigger event categories with reasonable reliability, with supervised machine learning achieving more stable performance than large language model approaches [12]. Multimodal studies have further shown that different trigger types produce qualitatively distinct response signatures: cognitive and emotional trigger events generate different patterns of linguistic alignment and physiological synchrony, confirming that the five-category taxonomy tracks real variation in group behaviour rather than serving as a purely conceptual classification [18]. Edwards et al. [21] operationalised the five trigger categories as detection rules applied to spoken discourse and found that groups could be prompted toward regulatory action when trigger events were externalised to them, though the effectiveness of this support depended on whether learners perceived the AI as a credible regulatory partner.

A gap remains, however. Existing approaches to trigger detection focus on classifying the content of trigger events at the category level. This content-level classification is a necessary first step, but it does not specify what has gone wrong in the group's shared regulatory processes as a result. Two groups may both be experiencing a cognitive trigger event, yet one may have lost a shared understanding of what the task requires, while the other has stopped monitoring whether their strategies are working [4]. These are distinct regulatory failures that may call for different forms of AI support at different moments. Without a systematic account of the group-level regulatory breakdowns that trigger events may produce, AI systems are not well positioned to determine whether intervention is warranted or what form it should take.

3. A Framework for Regulatory Breakdown in Trigger Episodes

This framework builds on the five trigger event categories established by Järvelä and Hadwin [9]. The first component draws on these trigger categories as the initiating conditions of the framework. The second, and central, component distinguishes three categories of group-level regulatory breakdown that trigger events may produce, each with observable discourse signals that could inform the timing and nature of proactive AI intervention. A single trigger event can lead to different breakdown categories depending on the group context, and a single breakdown category can be initiated by multiple trigger types.

3.1. Component One: Trigger Event Categories

Järvelä and Hadwin [9] identify five categories of trigger events in collaborative learning: cognitive, metacognitive, motivational, socioemotional, and behavioural. Drawing on this taxonomy, Table 1 consolidates definitions for each category from across the existing literature, providing a grounded characterisation of the initiating conditions the framework addresses.

Table 1
Trigger Event Categories in Collaborative Learning

Trigger Category	Description	Grounding
Cognitive	Difficulties in applying, elaborating, or connecting ideas, or negotiating multiple perspectives	[9, 14, 7]
Metacognitive	Difficulties in interpreting tasks, setting shared goals, or monitoring progress	[9, 14, 12]
Motivational	Discrepancies in members' goals, priorities, effort levels, or commitment to the collaborative task	[9, 14, 7]
Socio-emotional	Interpersonal tensions, negative affect, or relational friction arising from dysfunctional interaction styles, status asymmetries, or erosion of mutual trust	[9, 14, 12]
Behavioural	Declining or absent task engagement, participation imbalances, or coordination problems	[9, 14, 7]

Table 2
SSRL Breakdown Categories and Signals for Proactive AI Intervention

Breakdown Category	Definition	Observable Discourse Signals	Signal for AI Intervention Timing
Shared Task Perception Breakdown	Group members cannot negotiate or sustain a convergent understanding of the task or goals, such that collective regulation cannot begin	Divergent task interpretations without convergence; absence of consensus-seeking discourse; members proceeding on different assumptions without reconciliation; repeated re-explanation of the same task element without uptake	Sustained co-occurrence of contradictory task-focused utterances across members; absence of acknowledgement or uptake of others' task interpretations over an extended exchange
Metacognitive Monitoring Breakdown	The group loses collective awareness of its progress or strategy effectiveness, such that adaptive regulation becomes difficult	Absence of progress-checking discourse; failure to revise strategies despite stalled progress; absence of collective evaluation of the current approach; groups continuing on an unproductive path without self-correction	Extended absence of monitoring utterances following task-focused exchanges; task progression stalling without group acknowledgement; absence of reflective discourse following visible errors
Motivational-Socioemotional Breakdown	Imbalances in members' motivation, emotional states, or participation undermine the conditions that support shared regulation	Withdrawal of members from discussion; sustained dominance of a single voice without uptake; expressions of frustration or disengagement without regulatory response; absence of mutual acknowledgement; avoidance-focused interaction replacing task-focused exchange	Sustained decline in turn-taking reciprocity; negatively valenced utterances without co-regulatory response; persistent asymmetry in member contribution rates

3.2. Component Two: SSRL Breakdown Categories

SSRL breakdown categories describe group-level regulatory failures that trigger events may produce and that may warrant proactive AI attention. Each corresponds to a phase within the SSRL process [4] and is associated with observable discourse signals. We identify three categories (see Table 2).

The observable discourse signals in Table 2 are proposed on the basis of existing SSRL research and NLP work on collaborative discourse [12, 22, 5]. Their empirical validity as real-time detection signals for proactive AI systems remains to be tested.

4. Implications for Proactive AI Intervention Timing

Different breakdown categories may warrant different intervention thresholds. Shared task perception breakdowns tend to be particularly consequential early in collaboration, as divergent task understandings, if left unaddressed, may compound into further regulatory difficulties[4]. Metacognitive monitoring breakdowns are more likely to emerge during sustained task execution, when groups progressively lose the capacity to self-correct[7]. Motivational-socioemotional breakdowns can arise at various points and may call for relatively cautious intervention[5], as premature AI involvement risks further disrupting fragile group dynamics.

The framework suggests a two-step detection logic for proactive AI systems. Existing single-step classification approaches identify what kind of difficulty a group faces, but do not specify what has broken down in their shared regulatory processes. A system that first identifies whether a trigger event has produced a breakdown, then identifies the breakdown category, is better positioned to determine the form and timing of intervention. This approach is consistent with the two-step NLP detection architecture explored by Suraworachet et al. [12], and extends it by adding a diagnostic layer that specifies what kind of regulatory failure has occurred.

The observable signals in Table 2 also draw attention to the diagnostic relevance of absent discourse patterns. Monitoring utterances, consensus-seeking moves, and reciprocal acknowledgements are as informative in their absence as trigger-indicating utterances are in their presence. Proactive AI systems should therefore attend to both. At the same time, over-reliance on AI support risks undermining the regulatory agency that effective SSRL requires [23], and appropriate restraint in intervention design remains a parallel consideration.

5. Conclusion

This paper proposes a framework for understanding trigger events in collaborative learning from a proactive AI intervention perspective. Building on the five trigger event categories established by Järvelä and Hadwin [9], the framework identifies three categories of group-level regulatory breakdown that trigger events may produce, namely shared task perception breakdown, metacognitive monitoring breakdown, and motivational-socioemotional breakdown, each associated with observable discourse signals. By distinguishing trigger events from the regulatory breakdowns they produce, the framework enables more targeted decisions about when and how proactive AI systems should intervene in collaborative learning.

Several limitations apply. The observable discourse signals proposed in Table 2 are derived from existing SSRL research and have not been empirically validated as real-time detection signals; their reliability and specificity in authentic collaborative settings remain to be established. The framework was developed with educational collaborative learning contexts in mind, and its applicability to workplace or other collaborative settings requires further investigation. The relationship between trigger event categories and breakdown categories is treated here as analytically distinct, but which trigger types tend to give rise to which breakdown categories, and under what collaborative conditions, is an open empirical question.

Three directions would strengthen the foundations of this framework. First, empirical validation of the proposed discourse signals is needed, with the NLP methodologies developed by Suraworachet et al. [12] offering a useful starting point. Second, the mapping between trigger event categories and breakdown categories warrants systematic investigation across different collaborative contexts and age groups. Third, the appropriate form of AI intervention for each breakdown category requires design research: detecting a breakdown is a necessary but not sufficient condition for effective support, and the content, timing, and modality of AI feedback would need to be calibrated to the specific regulatory situation without undermining group autonomy [23]. We hope this framework contributes to ongoing discussions on proactive AI design by offering a group-level perspective on when intervention may be appropriate and, equally, when restraint is the more considered response.

Declaration on Generative AI

During the preparation of this work, the author(s) used generative AI tools, including GPT (OpenAI) and Claude Sonnet 4.6 (Anthropic), to assist with drafting, language refinement, and revision of manuscript text. Following the use of these tools, the author(s) critically reviewed and edited all generated content and take full responsibility for the integrity and accuracy of the final manuscript.

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