Trace-Based Indicators for Proactive AI Support of Socially Shared Regulation in Collaborative Writing

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Abstract

Effective collaboration requires socially shared regulation of learning (SSRL), yet regulatory difficulties often remain invisible in online environments. To support proactive and reflective learning without reducing learner agency, AI systems need interpretable signals that identify when groups may benefit from timely scaffolding. This paper operationalizes SSRL challenges using trace-based indicators in collaborative writing. Using log data from 285 student groups (N = 1690), we develop indicators for five challenge types. Results suggest that behavioral traces can provide interpretable signals of potential regulatory difficulties. While these indicators do not directly measure SSRL processes, they make otherwise hidden aspects of collaboration visible. We discuss how such signals can inform adaptive support, particularly through AI-based conversational agents. This paper contributes a set of operationalized, explainable trace-based indicators for SSRL challenges and an empirical demonstration of their applicability in large-scale collaborative writing data.

Keywords

socially shared regulation of learning, learning analytics, collaborative writing, proactive learning support, AI in education

1. Introduction

Collaborative learning is important in higher education, but group work does not automatically result in effective collaboration [1]. A key component is socially shared regulation of learning (SSRL) [2], which is crucial for effective collaboration [3].

Measuring SSRL is challenging because regulatory processes are not directly observable. While trace-based approaches are established for self-regulated learning [4], their use for SSRL is still limited [5], particularly in online settings. Digital learning environments enable the collection of fine-grained behavioral trace data that can provide insights into collaborative processes [6]. Such indicators can support adaptive systems, including AI-based conversational agents that prompt reflection and coordination. However, AI interventions need to be carefully designed to preserve student and teacher agency [7].

SSRL challenges can hinder collaboration but also create learning opportunities [8]. Challenges have been recognized as especially relevant for regulation, as groups' regulation should be judged based on how they respond to problems. Hadwin et al. identified five challenge categories: planning, doing the task, checking progress, group work and running out of time [8]. However, it remains unclear how they can be operationalized using trace data. We address this gap by proposing indicators for five selected SSRL challenges that can be approximated using behavioral data without requiring content analysis. Indicators are applied on real-world large-scale course data, contrasting commonly used small lab studies [9].

How can different ideas about how to start *(RQ1)*, different levels of commitment to the task *(RQ2)*,

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different ideas about when to check progress *(RQ3)*, unequal participation or distribution of work *(RQ4)* and running out of time *(RQ5)* be operationalized using trace-based indicators in collaborative writing?

This paper proposes trace-based indicators for SSRL challenges and demonstrates their application using log data from a large-scale collaborative writing course. The indicators provide interpretable behavioral proxies for potential regulatory challenges and a basis for adaptive AI-supported interventions [10]. Importantly, these indicators are meant to serve as behavioral proxies for possible challenges, to then support and encourage reflection.

2. Methods

The dataset comprised 285 collaborative writing groups (N = 1690 students) enrolled in an undergraduate psychology course at [removed for blind review]. Students completed a mandatory collaborative writing assignment in a Moodle-integrated Etherpad environment. Groups (3–8 students, M = 5.93) worked on two three-week writing phases summarizing different sections of a research paper. In total, the trace dataset contained over 3,375,546 text-edit events (adding, deleting, formatting), 1,016,367 scroll events, 8395 chat messages, 1765 comments and 1237 comment replies, all collected in the winter semester 2023-2024. Communication outside the Etherpad (e.g., Moodle forums or external tools) was not captured. In addition, a two-week initial get-to-know phase preceded the analyzed writing phases and is not included in the dataset.

For each research question, we defined trace-based indicators to operationalize the respective SSRL challenge. Across indicators, inequality within groups was quantified using the Gini coefficient [11]. Since no established thresholds exist for interpreting inequality in trace-based SSRL indicators, we adopt a distribution-based approach. Groups above the 75th percentile were classified as high dispersion; for inverse indicators, groups below the 25th percentile were flagged. This percentile-based cutoff allows identifying a manageable subset of groups for adaptive support while remaining sensitive to cohort-specific distributions. These thresholds are intended as configurable decision aids rather than fixed automated decisions.

RQ1: The first phase in successful SSRL is planning, allowing groups to set shared goals, plans and standards [8]. Early alignment or misalignment can set the tone for the rest of collaboration. Start behavior was operationalized using activity during the first week. For each student, a start-style ratio (messages / (added characters + 1)) captured the balance between discussion and writing. Inequality in start strategies was quantified using the Gini coefficient within groups. If groups do not share their understandings or plans with each other, they can struggle with task fulfillment [8]. To approximate explicit planning, groups were classified as chat-first (chat before writing), silent-start (writing before chat), no-writing or no-chat. Mutual awareness and shared pacing could also be deferred by temporal alignment of starts, with widely separated starts indicating weak coordination. Temporal alignment was measured using start-time dispersion, defined as the standard deviation of delays between each student's first activity and the group's first activity (capped at one week). Groups exceeding the 75th percentile of the dispersion distribution were classified as showing high start-time dispersion.

RQ2: Commitment in collaborative writing is not only reflected by total output, but by sustained engagement over time [12]. SSRL requires members to remain engaged across planning, drafting, revision, and coordination phases. Continued involvement in the shared task can be approximated through active days per student, defined as days with at least one interaction (edits, chat messages, comments). Students disengaging from the task before all others are finished, deny the group shared monitoring, adaption or reflection, thus also showing reduced commitment to the task. To capture disengagement, a drop-off indicator measured the time between a student's last activity and the group's last activity.

RQ3: In SSRL, monitoring has to happen at the right point in time in order to be effective [2], a lack of alignment regarding this temporal aspect can thus hinder SSRL. Monitoring behavior was approximated using scroll-based review sessions. Scrolling through the shared document with little concurrent writing likely reflects reading, inspecting prior contributions or reviewing task progress. Sessions were defined as consecutive scroll events separated by less than five minutes, excluding sessions with more than 100 characters added. Given that 50% of sessions involve fewer than 100 characters, the threshold effectively separates low-level editing behavior from more extended writing contributions. For each student and week (relative to the writing phase), the average timing of review activity was calculated as hours since the start of the respective week, capturing temporal dynamics of monitoring [9]. Temporal misalignment was quantified as inequality in review timing within groups per week.

RQ4: Participation plays an important role in SSRL, as uneven participation can limit the opportunities for successful collaboration [13]. Participation inequality was measured across three indicators: writing volume (characters added), edit frequency, and chat message frequency. Writing volume captures participation on the central task product and has been used previously to capture participation equality [13]. Edit frequency complements writing volume as participation can also include behaviors such as refinements or formatting. Finally chat message frequency captures aspects of collaboration like planning, negotiation or socioemotional interactions. Communication imbalance may therefore reflect unequal involvement in regulatory and decision-making processes, even when writing contributions appear balanced. Inequality within groups was quantified using the Gini coefficient.

RQ5: Time management can be seen as prerequisite for SSRL, as a lack of time limits time for planning, coordination or reflection. Task progress over time allows more insights than just the final task product, as groups might still experience problematic delays or reduced opportunities for revision. Running out of time was operationalized as delayed writing progress relative to the cohort at a daily level. Comparing against the cohort mean allows for a task context-specific pacing. Cumulative writing output per group was computed per day and divided by the cohort mean on the same day, including groups with no activity (treated as zero output). To reduce sensitivity to initial inactivity, the first three days of each phase were excluded. For each group, the mean progress ratio across the remaining days was calculated. Groups in the lowest quartile were classified as showing delayed progress.

The proposed indicators were derived theoretically from SSRL challenge categories described by Hadwin et al. [8] and translated into observable behavioral traces available in collaborative writing logs. The indicators therefore represent theory-informed proxy measures rather than validated diagnostic measurements. Multiple indicators were used for several challenge categories to reduce dependence on single behavioral assumptions. Table 1 gives the metric and interpretation for each indicator.

3. Results

Across the course, students produced over 14 million characters in more than 3 million editing events. Chat participation was low (M = 4.97 messages per student), while students added on average M = 8,520.63 characters to the written text.

RQ1: Early collaboration activity was limited. Only 511 students contributed writing during the first week (M = 2.45 active writers per group), and only 30.24% sent a chat message. While 233 groups used the chat at some point, only 97 did so in the first week. Most groups began writing without prior discussion: 77% started writing before the first chat message, 18% never used chat, and only 4.6% initiated collaboration via chat. No groups chatted without writing. Among groups that later used chat, substantial text was produced before the first message (Md = 4,262 characters). Start-style inequality ranged from 0.00 to 0.88 (M = 0.37, SD = 0.40), with most groups showing moderate divergence. Start-time dispersion (SD) ranged from 10.72 seconds to 80 hours (M = 30.13 hours, SD = 20.01 hours), with 25.36% of groups exceeding the threshold for high dispersion. Most groups started with a silent start, without showing high dispersion for the other indicators (51.43%). A substantial number of groups also showed high dispersion for start time (22.38%) or start style (16.67%) in combination with a silent start. Only 3.81% started silently and showed high divergence for both other indicators.

RQ2: Students were active on between one and 26 days (M = 5.45, SD = 3.27). Inequality in active days was moderate (M = 0.23, SD = 0.08), indicating relatively similar engagement patterns within groups. In contrast, drop-off durations showed higher inequality (M = 0.50, SD = 0.13), suggesting differences in sustained commitment. Most groups did not show high inequality for either indicator (56.49%), about

Table 1
Trace-based indicators operationalizing potential SSRL challenges

Indicator	Metric	Interpretation as proxy indicator
Different ideas about how to start		
Start-style inequality	$\mathrm{Gini}\left(\frac{\text{messages}}{\text{added chars}+1}\right)$ during week 1	Divergent approaches to initiating collaboration (discussion vs. immediate writing).
Start-mode classification	Chat-first, silent-start, no-writing, or no-chat	Limited explicit planning or coordination before task work.
Start-time dispersion	SD(first activity delay)	Weak temporal coordination or delayed onboarding of members.
Different levels of commitment		
Active-day inequality	Gini(active days)	Unequal sustained engagement across collaboration phases.
Drop-off inequality	Gini(last activity delay)	Some members disengage substantially earlier than others.
Different ideas about when to check progress		
Monitoring-time dispersion	Gini(review timing)	Misaligned monitoring and review practices within the group.
Unequal participation or distribution of work		
Writing-volume inequality	Gini(added characters)	Uneven contribution to the shared task product.
Edit-frequency inequality	Gini(edit events)	Uneven participation in revising or refining the artifact.
Message-frequency inequality	Gini(chat messages)	Unequal participation in planning, negotiation, or socioemotional interaction.
Running out of time		
Delayed progress ratio	$\mathrm{Mean}\left(\frac{\text{group output}}{\text{cohort mean output}}\right)$	Delayed pacing and reduced time for coordination or revision.

Note. Gini = within-group inequality coefficient; SD = standard deviation. Review sessions were defined as consecutive scroll events separated by less than five minutes and involving fewer than 100 added characters. The delayed progress ratio excluded the first three days of each writing phase.

equal amounts showed high inequality for only drop-off (18.95%) or active days (18.6%), only 5.96% were flagged for both indicators.

RQ3: Monitoring behavior showed moderate temporal dispersion (M = 0.25, SD = 0.15). However, 25.1% of group-weeks exceeded the threshold for high dispersion. This suggests that while most groups exhibited relatively aligned monitoring behavior, a substantial proportion showed notable temporal dispersion in review activity.

RQ4: Separate Gini indices were computed for writing volume (M = 0.33, SD = 0.11), edit frequency (M = 0.41, SD = 0.13), and message frequency (M = 0.66, SD = 0.16). Many groups were not flagged for any indicators (38.5%) or were not flagged for any while sending no messages (9.8%), similar amounts were flagged for only single indicators (high message frequency imbalance: 10.5%, high volume imbalance: 10.1%, high edit frequency imbalance: 8.4%). Only 2.8% of groups showed high inequality across indicators.

RQ5: Progress ratios varied widely across groups (Min = 0.00, Md = 0.74, Max = 31.5), indicating substantial differences in pacing. Using the distribution-based threshold, 24.9% of groups were flagged as delayed in each phase. Overall, 37.2% of groups were flagged in at least one phase. While the same proportions of groups were flagged in both phases, only 12.6% were identified in both, suggesting that delayed progress is partly phase-specific rather than a stable group characteristic.

4. Discussion

4.1. Descriptive Indicator Results

This study developed and explored trace-based indicators for SSRL challenges in collaborative writing and examined their potential to inform explainable AI-supported interventions. Overall, the results show that behavioral traces can provide interpretable signals of potential regulatory challenges, while also highlighting differences in how clearly these challenges manifest in trace data. For different ideas about how to start *(RQ1)*, most groups showed low divergence in start strategies and relatively aligned start times. The prevalence of silent starts may suggest that groups often begin working without explicit coordination. This may indicate limited shared planning, which has been associated with reduced task performance [8], but planning may also have occurred in the previous phase or on other channels.

For different levels of commitment to the task *(RQ2)*, inequality in active days was generally low, while drop-off behavior showed greater variation. This suggests that groups often show similar overall participation patterns but differ in sustained engagement within the Etherpad environment over time. Such patterns may lead to situations where some members disengage early, potentially limiting opportunities for feedback and coordination.

For different ideas about when to check progress *(RQ3)*, scrolling behavior showed moderate temporal dispersion, indicating that most students tended to review progress at similar times. This aligns with prior findings that checking progress is less frequently perceived as a challenge [8]. However, the presence of misaligned group-weeks suggests that differences in monitoring still occur and may affect coordination.

For unequal participation or distribution *(RQ4)*, we looked at three different indicators. Highest inequality was observed regarding message frequency, which could signal unequal participation for planning and discussions. While most groups were not flagged for any of the indicators, a substantial number were flagged for individual indicators, highlighting that unequal participation is a multi-dimensional phenomenon.

For running out of time *(RQ5)*, delayed writing progress relative to the cohort identified groups at risk of falling behind. This indicator also identified groups falling behind in one or both phases. In previous work running out of time was the most common perceived challenge [8], while we did not evaluate students' perception, our data shows the relevance of this challenge.

4.2. Implications for Interventions

Across challenge categories, the proposed indicators demonstrate that SSRL processes can be approximated through behavioral traces, providing a basis for identifying critical moments in collaboration. The proposed indicators could be transferred to other collaborative contexts by for example generalizing writing volume to volume of artifact work or message frequency to communication frequency. The indicators can serve as signals to trigger adaptive, non-directive interventions that prompt reflection and alignment of collaboration processes. Building on Hadwin et al.'s categorization of collaboration challenges and reported regulation strategies, trace-based indicators can be linked to agency-preserving prompts that invite reflection and collaborative decision-making rather than prescribe actions. Table 2 illustrates examples.

AI-based conversational agents are particularly suitable for SSRL support because they can embed interventions within ongoing collaboration processes through adaptive dialogue rather than static notifications or predefined scripts. While the existing learning environment already includes dashboards with group metrics, dashboards require learners to actively access and interpret the information themselves. Conversational agents can instead provide proactive and contextualized prompts directly within collaboration processes, potentially reaching groups that would otherwise not seek support. In addition, agents can explain why challenges were detected and suggest possible regulation strategies while maintaining learner agency.

By linking interpretable trace-based indicators to targeted prompts and explanations, AI-based conversational agents can support regulation in a context-sensitive and understandable manner. Im-

Table 2
Exemplary agency-preserving AI interventions grounded in Hadwin et al. [8]

Challenge	Strategy category	Exemplary intervention message
Different ideas about how to start	Planning	Your group may be approaching the task differently. Would it help to briefly align on goals and priorities?
Different levels of commitment to the task	Planning and checking	Recent activity suggests commitment may be declining for some members. Would it help to revisit your shared goals or check what support is needed to keep progress moving?
Different ideas about when to check progress	Planning and doing	Your group members appear to review progress at different times. Would it help to briefly align on when to pause for review or discuss your individual expertise and tips regarding reviewing?
Unequal participation or distribution of work	Planning	Contributions to writing or discussion appear imbalanced. Would you like to revisit task understandings and set goals?
Running out of time	Planning and checking	Progress seems slower than expected for this stage. Would reviewing milestones or adjusting your approach help you use the remaining time well?

portantly, such interventions can adapt dynamically based on group responses, allowing support to evolve alongside the collaboration process. To support balanced human and AI agency, AI agents should prompt reflection rather than giving commands, also improving socioemotional interactions [14]. Similarly, students need to remain in control of whether to follow suggested strategies, to adapt them or to follow different approaches. Excessive co-regulation needs to be prevented as it can hinder groups from developing shared goals or strategies for task work [15]. Instructors need to be included in the development of indicators and interventions and be able to adapt them to the learning environment at hand.

4.3. Limitations and Outlook

Several limitations should be considered. First, the use of the integrated chat was limited, and it is unclear whether this reflects low communication or a shift to external tools. Additionally, a preceding two-week get-to-know phase was not included, potentially omitting early coordination and relationship-building processes. Second, the proposed indicators represent theory-informed behavioral proxies rather than direct measurements of SSRL challenges and therefore require further validation. Similar behavioral patterns may reflect different collaborative processes depending on context. For example, unequal participation may also emerge from productive role specialization, while silent starts may reflect coordination through external communication channels. Future work should therefore triangulate the indicators with process-oriented data such as self-reports, observations, qualitative coding, and collaboration outcomes to evaluate construct validity and reduce risks of misclassification. Third, this study focused on one challenge per category. Future work could extend this to additional challenges, potentially combining trace data with content-based analyses. Future research should also investigate how these indicators interact with regulatory strategies over time [10] and evaluate whether interventions based on them improve collaboration and learning outcomes.

This study investigated how potential SSRL challenges can be approximated through trace-based indicators in collaborative writing. We developed indicators for five SSRL challenges and demonstrated how behavioral traces can provide interpretable signals of potential regulatory challenges. Unlike opaque black-box predictions, the proposed indicators are transparent and explainable, allowing learners and teachers to understand why support is triggered. The results suggest that patterns such as misaligned starts, uneven commitment, asynchronous monitoring, participation imbalances, and delayed progress can be approximated through trace data. These findings highlight the potential of trace-based indicators as a foundation for adaptive support. This positions trace-based indicators as a practical foundation for human-centered, proactive AI systems that strengthen rather than replace learner and teacher agency.

Declaration on Generative AI

During the preparation of this work, the author(s) used Chat-GPT-5.3 in order to: Grammar and spelling check. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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