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Deliberative Interactions for Socially Shared Regulation in Collaborative Learning: An AI-Driven Learning Analytics Study

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Abstract

Socially shared regulation in learning (SSRL) contributes to successful collaborative learning (CL). Empirical research into SSRL has received considerable attention recently, with increasingly available multimodal data, advanced learning analytics (LA), and artificial intelligence (AI) providing promising research avenues. Yet, integrating these with traditional datasets remains a challenge in SSRL research due to the misalignment between theoretical constructs, methodological assumptions, and data structure. To address this challenge and expand our understanding of the nature of SSRL, the present research adopted a human–AI collaboration approach in a three-layer analysis to examine group interactions in response to cognitive and emotional regulation triggering events. Two-level theoretical lenses — macro-level (regulatory aspects) and micro-level (deliberative interactions) — were used to analyze 2,125 utterances from video-recorded tasks of ten groups of three Finnish secondary students (N=30). Results showed two types of deliberation patterns for SSRL, namely 1) the Plan and Implementation Approach (PIA) associated with adaptive patterns, and 2) the Trials and Failure Approach (TFA) associated with maladaptive patterns. Our findings revealed that groups often fail to recognize, or are ill-equipped to respond to, emerging regulatory needs. These findings advance SSRL theories and research methodologies by utilizing AI-enhanced LA to offer new insights into group dynamics and regulatory strategies.

Notes for Practice

- Learning analytics (LA) and artificial intelligence (AI) present opportunities to unravel the temporal dynamics and complexities of socially shared regulation in learning (SSRL), yet challenges also emerge in integrating these advanced techniques with traditional research methods and constrained datasets. This study provides a demonstration of how LA/AI can be utilized to bridge this gap.
- Leveraging SSRL literature, AI-driven analysis methods, and a micro-lens of deliberation, we provide the first understanding of how group deliberative characteristics manifested in response to different regulation triggering events and answer to the call for research regarding the challenges of data granularity.
- Our identification, characterization, and modelling of two adaptive and maladaptive collaborative interaction patterns, across quantitative, structural, and sequential attributes, impact the design and development of LA/AI and educational technologies. Findings support the real-time detection and analysis of group deliberation patterns. This enables early predictions of group dynamics and regulatory responses, which can be leveraged to guide and motivate students toward more effective strategies.

Keywords: Socially shared regulation of learning (SSRL), learning analytics (LA), artificial intelligence in education (AIED), epistemic network analysis

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1. Introduction

In light of today's rapid digital transformation and global interconnectivity, socially shared regulation in learning (SSRL) has increasingly become a central construct for understanding collective social interactions and collaboration for learning success, making it important for research and practice (Hadwin et al., 2018; Järvelä et al., 2018). Several empirical findings have shown that in collaborative learning (CL) contexts, all three types of regulation: self-regulated learning (SRL), co-regulated learning (CoRL), and SSRL emerge. SSRL, in particular, has been viewed as one of the vital processes for CL success since it refers to groups regulating together as a collective, such as constructing shared task perception, setting goals, or aligning interests. It entails the metacognitive process of monitoring and taking control of their group cognition, motivation, and emotion through reflection, deliberative negotiation, and continual adaptation. Deliberation, by which we mean to refer to the deliberative, negotiation characteristic of interactions for regulation in CL contexts, is hence, as SSRL theories posited, one of the key mechanisms for adaptive regulation. We choose the term "deliberation" for its distinctive emphasis on convergent interests and a shared nature (Ihnen, 2014). These individual and social forms of regulation processes intertwine and mutually reinforce one another, interacting with the group's dynamic situational challenges and the regulatory skills or strategies used by group members (Järvelä et al., 2018). This means that adaptation and its deliberation mechanisms occur at multiple proximal levels, interacting and affecting one another (Bakhtiar & Hadwin, 2020). Despite its centrality to the collaborative interactions involved in regulation, there is a lack of empirical research that examines the micro process of deliberative negotiation in SSRL. Accordingly, this study aims to fill this gap.

Nevertheless, due to the complex and non-observable nature of cognitive and emotional processes at the core of SSRL, identifying and measuring this phenomenon has been a major challenge (Järvelä & Bannert, 2021). SSRL, which builds upon and extends the individual model of SRL (Winne & Hadwin, 1998) to a social one, involves group members strategically taking control of their learning engagement and situations through active cycles of planning, performance, and reflection. Thus, SSRL is a temporal, multidimensional (motivational, emotional, behavioural, and cognitive) dynamic, and a cyclical process of monitoring and adapting (Hadwin et al., 2018). Such characteristics of SSRL challenge the capacity of traditional research methods such as self-reports to fully model and monitor the non-linear and dynamic constructs of SSRL and the human learning mechanism in collaborative settings (Cukurova et al., 2020).

In learning sciences, video-based analysis and multimodal learning analytics (LA) have shown promising potential to overcome the shortcomings of traditional methods and to be more beneficial for understanding different dimensions of this social phenomenon (Andrade et al., 2016; Cukurova et al., 2020; Järvelä & Bannert, 2021). These data-driven tools and techniques have provided new data modalities and opened novel analytics methods to capture and examine the "invisible" emotional and cognitive processes at the centre of human regulation. While exploratory in nature, current methodological advancements in the study of learning regulation are crucial for advancing the field, offering micro-level data points and markers that can refine our understanding of the phenomenon (Dawson et al., 2019).

However, these new data modalities and advanced techniques might not directly align with the theoretical understanding of SRL and SSRL as grounded in metacognitive awareness situated in self, group, and task conditions that result in strategic responses (Järvelä, Nguyen, & Hadwin, 2023). Much of the research still relies on traditional methods such as self-report and other subjective measures (i.e., coding of verbal protocols and/or video). Efforts to integrate this qualitative data with new channels and analytical techniques have been made (Järvelä, Nguyen, Vuorenmaa, et al., 2023; Molenaar et al., 2023). However, in part due to the resource-intensive nature of processing data at a more granular level, this qualitative information is often collected and analyzed from a more macro perspective (i.e., at the 30-second segment or meaningful episode). This approach may pose challenges in fully synthesizing and triangulating data from different modalities, and may also fail to meet the assumptions required for applying advanced LA and AI techniques (Nguyen et al., 2022). These disparities lead to a current lack of engagement between theoretical concepts, data structure, and methodological assumptions, risking an oversimplification of the actual dynamics and temporal complexities of SSRL, and undermining the validity and reliability of the research (Chen et al., 2020). Capturing microanalytical qualitative information with a high level of detail is crucial for analyzing data across multiple timeframes and integrating it with advanced analytical methods to better understand SSRL. However, a more focused theoretical framework is required to effectively encode this detailed qualitative information.

To better operationalize and capture the temporal complexities of SSRL, the present study takes a granular approach with a micro-lens of deliberation at millisecond timestamps. This approach is realized through a human–AI collaborative three-layered analysis integrating an AI algorithm to granularly examine sequences of group-level interactions in response to regulatory triggers. A regulatory trigger is defined as a motivational, cognitive, emotional, or behavioural condition that warrants regulatory action or response to the event that hinders task progress and necessitates the adaptation of current regulatory practices or strategies (Järvelä, Nguyen, & Hadwin, 2023). The AI-enabled micro approach focuses on the deliberation process, allows us to capture the complexity and dynamism of group interactions for regulation in a more nuanced manner, and aligns with the granularity expected in the following analysis techniques (Järvelä, Nguyen, & Hadwin, 2023). Our research questions are as follows:

1. What type of group deliberative characteristics are manifested in response to different regulation triggering events?
2. What are the patterns of group deliberative characteristics in response to different regulation triggering events in collaborative learning tasks?

2. Background

2.1. Deliberation in Socially Shared Regulation of Learning (SSRL)

Self-regulation in learning entails a multidimensional process in which learners actively control and manage their cognitive, emotional, motivational, and behavioural resources to achieve learning outcomes (Winne & Hadwin, 1998). SRL, in social contexts, is also socially situated and shared, involving dynamic interplay with other learners, teachers, parents, as well as the task, contexts, and cultures (Järvelä & Bannert, 2021). The growing importance of CL has concurrently fuelled the research interest in understanding the mechanisms through which groups regulate their learning behaviours and activities (Järvelä et al., 2018; Molenaar et al., 2023).

Despite the benefits of CL, such as promoting motivation, engagement, social skills, and knowledge constructions, its success is not inherent. Previous research has established that, in practice, groups and individuals face a variety of challenges that can impede both the social process of learning and task completion (Hurme et al., 2015). These can originate from individual differences, interpersonal dynamics (Järvenoja et al., 2020; van den Berg et al., 2014), or cognitive-related processes, such as establishing shared understanding, setting goals, or negotiating multiple perspectives (Vuorenmaa et al., 2023). Overcoming these challenges requires students to engage in the regulation of learning by monitoring, controlling, and redirecting their group's collective cognitive and socio-emotional processes.

Within CL, various challenges, difficulties, and conflicts serve not only as obstacles but also as triggers for SSRL. The broadening contexts from individual to group level introduces not only varied cognitive structures, emotional states, and motivational perspectives of individual members but also complicated social dynamics and interpersonal relationships into the learning process (Järvenoja et al., 2020). This increases the number of potential interactions and complexities (Hurme et al., 2015) resulting in various external (i.e., task, resources, team dynamics) and internal (i.e., work ethics, personalities) factors that contribute to conflicts, challenges, and negative incidents in collaborative contexts (Gelfand et al., 2014), meaning that the group requires regulation (Järvenoja et al., 2020; Näykki et al., 2021).

The process of deliberative negotiation thus serves as a key mechanism for setting the stage for and inviting regulation, which in this study is refined and formally referred to as "deliberation." The term "deliberation" is chosen over "negotiation" for a specific reason. Unlike negotiation, which focuses on resolving conflicts through compromise, deliberation emphasizes discussing and evaluating diverse perspectives to reach a well-informed, thoughtful decision (Ihnen, 2014). This focus on shared understanding and mutual interests aligns more closely with the goals of SSRL and fits better within the broader context of CL. Deliberation thus, as conceptualized in this study, encompasses a structured exchange of ideas, a thorough evaluation of evidence and arguments, and the negotiation of differences (Walton, 1998). As such, it might seem that deliberation shares certain similarities with processes in collaborative problem-solving (CPS). Nonetheless, we argue that they should not be considered synonymous. CPS primarily focuses on the resolution of problems. Research in this area has largely been devoted to identifying the collaborative processes that contribute to successful outcomes (Meier et al., 2007). In contrast, deliberation focuses on the qualitative nature and characteristics of interactions between group members, exploring how these interactions contribute to shared understandings or co-constructed adaptations of various cognitive, emotional, motivational, and behavioural aspects in the learning process. Since research has demonstrated that group regulatory processes vary with differing levels of challenge (Bakhtiar & Hadwin, 2020), exploring the characteristics of deliberation patterns in the CL interactions responding to them may bring to light critical features of strategic actions that may be more adaptive for learning.

2.2. Trigger Concept and the Human–AI Shared Regulation in Learning (HASRL) Model for SSRL

SSRL is a complex and multidimensional adaptive process. Characterizing as well as possible the mental processes underlying this psychological phenomenon requires advanced analytics, methodologies, and multimodal data (e.g., behavioural, physiological, and representational data; Cukurova et al., 2019). Following the SRL theory-guided trigger event framework developed by Järvelä, Nguyen, and Hadwin (2023), different data modalities will be leveraged with AI-based methods to shed light on specific triggering events that invite regulatory processes. Investigating how groups and individuals dynamically regulate various aspects of the group task involves examining the specific interaction process that unfolds during regulatory episodes. Such an undertaking often requires researchers to engage in detailed transcribing and coding of group member utterances (Bakhtiar & Hadwin, 2020). This span across multiple facets (i.e., type of regulation, target of regulation) and layers — including processes of metacognitive, cognitive, motivational, and emotional interactions (i.e., interactions for regulation) — underlies the regulatory episodes (Isohätälä et al., 2017; Nguyen et al., 2023).

In the context of group learning, these specific instances, or "triggering events," refer to specific circumstances that necessitate regulatory actions, such as intra-group disagreements or conflicts. As explained by Järvelä, Nguyen, and Hadwin (2023), multimodal data (i.e., audio, video, physiological, behavioural, discourse, et cetera) surrounding triggering events carry signal and empirical evidence of the need for regulatory response caused by the learner's internal, external, or contextual conditions. For example, Nguyen et al. (2023) identified physiological arousal among group members as an indicator of metacognitive regulation. In another study, Sobocinski et al. (2020) utilized coded video data and shifts in heart rate to distinguish between adaptive and maladaptive regulation in collaborative settings. More recently, Dang, Nguyen, et al. (2023) deployed AI-driven facial emotion recognition tools to explore the interplay between transitional emotional states and emotional self-regulation within real-time learning environments. Identifying these signals not only facilitates the tracing, modelling, and prediction of the regulatory processes and patterns in CL (Järvelä, Nguyen, & Hadwin, 2023) but also enables the comparison and analysis of adaptive and maladaptive regulatory responses that follow the triggers.

While the trigger framework is effective in locating SSRL signals, the Hybrid Human–AI Shared Regulation in Learning (HASRL) model (Järvelä, Nguyen, & Hadwin, 2023) built upon this framework and advanced data analytics (Nguyen et al., 2020). HASRL plays a pivotal role in creating a common language and understanding that bridges human learning with AI machine learning operations. This model facilitates a synergistic understanding, viewing human and AI regulatory systems as interconnected elements of an advanced hybrid intelligence framework. It aims to design a human–AI shared regulation system that leverages human strengths and compensates for human limitations.

This study specifically focuses on the human regulatory system within the HASRL model to analyze how it responds to regulatory triggers. While the research does not involve designing an AI system for HASRL, the insights gained from our human–AI collaboration approach aim to enhance theoretical knowledge for future system development and lay the groundwork for processes within HASRL. Moreover, this approach is particularly adept at alleviating the labour-intensive aspects of processing micro-level data points and aligning these data with advanced AI methodologies for a more refined analysis, thereby offering deeper insights into the intricate dynamics and complexities of SSRL.

3. Methods

3.1. Research Context and Participants

The study took place within a controlled laboratory setting, with 30 Finnish secondary students (21 males, 9 females) divided into 10 triads. Students seated at individual desks arranged in a triangle-like formation and engaged in a collaborative task using a shared Google document accessible to all participating teams (see Figure 1). They were asked to plan a healthy breakfast smoothie based on the nutritional requirements provided within the document. The task lasted for 30–40 minutes.

Previous studies have shown that SSRL rarely occurs in typical learning contexts without certain triggers (Nguyen et al., 2023; Ucan & Webb, 2015). Given the one-time nature of our task, specific triggering events simulating real-world challenges

Figure 1. Collaborative learning setup.

were introduced to ensure the presence of moments that necessitate regulatory actions. This, in turn, will also facilitate the location and observation of how students adapt and regulate their behaviour in response to cognitive and emotional challenges. Accordingly, halfway through the task, each group received a manipulated cognitive triggering event: a voice message from a customer mentioning an allergy. This was intended to challenge student cognitive abilities to adapt their plans based on new information. This is followed by three emotional triggers at 3-minute intervals, involving the customer expressing their increased negative emotional valance — from mild impatience, advancing to urgency, and finally to annoyance. These emotional triggers aimed to create a socio-emotional challenge, requiring students to manage their emotions, motivation, and maintain effective collaboration under pressure. The current research dataset consisted of ten high-quality video and audio recordings, collected from each group using Insta360 Pro video cameras, individual microphones, and a group microphone placed at the centre of each group.

3.2. Data Analysis: Analytical Procedure and Methods

We employed an AI-enhanced three-layered analysis (see Figure 2) to examine the regulatory and deliberative characteristics of group interactions in response to different triggering events in collaborative learning. Since collaborative learning is a complex and adaptive process, Ouyang, Xu, and Cukurova (2023) extend investigations into the use of AI-driven LA to understand the multimodal, dynamic, synergistic characteristics of group collaborative patterns during complex tasks. By adopting an innovative approach within the context of SSRL research and further integrating Järvelä, Nguyen, and Hadwin's (2023) human–AI collaboration approach, this study implements a three-layer framework to examine the deliberative characteristics of interactions in SSRL. Within this framework, AI algorithms were incorporated into different layers using multiple LA approaches. Layer 1 employed AI-enabled techniques for auto-transcribing and segmenting student discourse, facilitating fine-grained qualitative coding of regulatory (Appendix 1) and deliberative characteristics (Appendix 2). This step is essential as it not only utilizes AI to reduce manual labour but also generates micro-segmentation of data that is suitable for further machine learning techniques. Layer 2 involved temporal sequence analysis to identify clusters of deliberation patterns based on similarities in group sequences during triggering events. Lastly, Layer 3 employed statistical analysis, epistemic network analysis, and process mining to examine the character and relationship between deliberation patterns and group regulatory characteristics in response to these events.

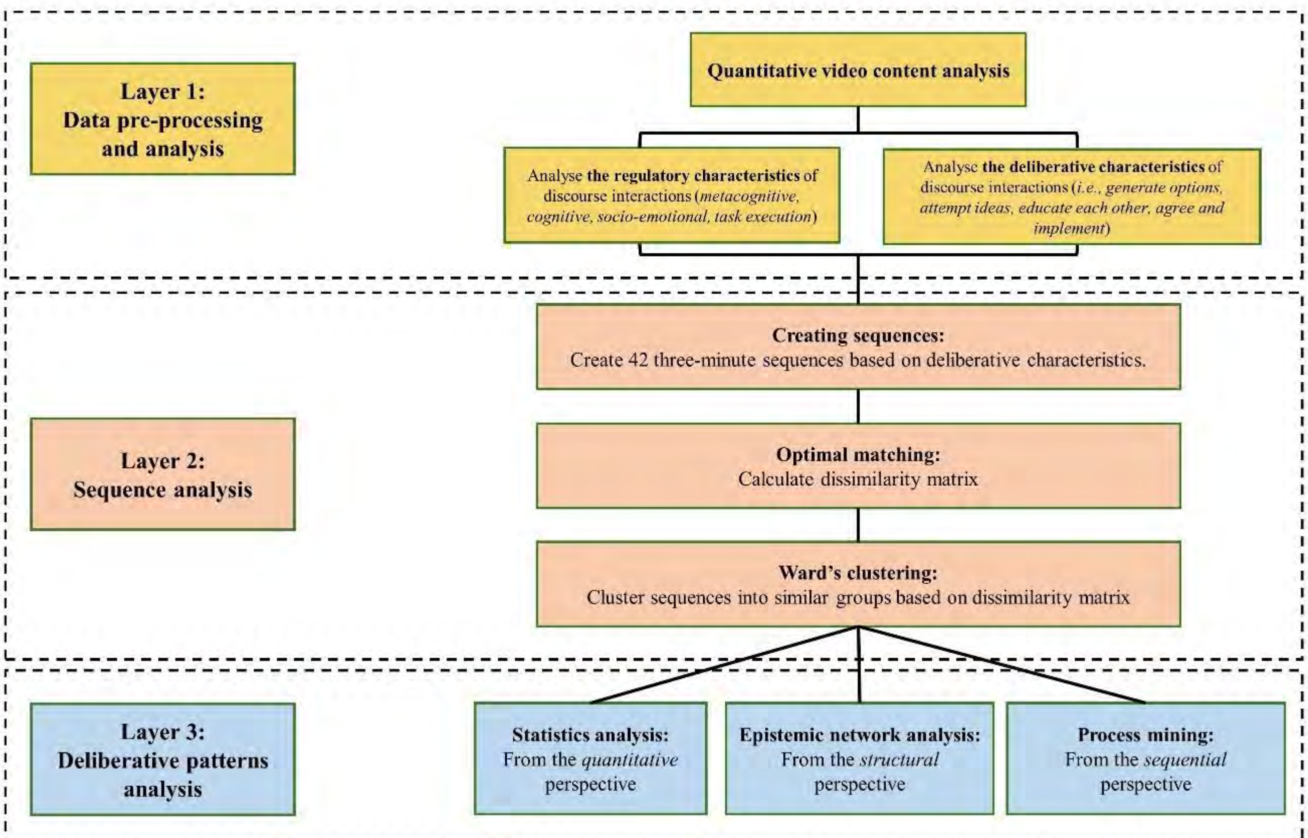

Figure 2. The human–AI collaborative three-layered analysis (adopted from Ouyang et al., 2023).

3.2.1. Layer 1: Data Pre-Processing and Analysis

The recorded audio was auto-transcribed and segmented by AI-enabled micro-analytical recording techniques and then cross-checked by two native-speaking researchers for accuracy. Our coding, aimed at understanding the deliberative and regulatory response to triggering events, spanned from three minutes before to three minutes after each trigger. The adopted unit of analysis was turns of individual student utterances. However, the analysis decision for the code was made in the larger context of the team discussion to capture the group-level interactions, with a context window of 7–10 turns. Each utterance was labelled for both regulatory (e.g., metacognitive, cognitive) and deliberative characteristics (e.g., option generation, education). It is important to note that the context window for regulatory characteristics may differ from that of deliberative characteristics.

To capture the complex and abstract phenomenon of SSRL suitable for AI analysis, we applied two coding schemes: one for high-level SSRL characteristics and another for low-level deliberative characteristics. While the concept of SSRL operates at a more abstract level, specific patterns of deliberation are within a more quantifiable dimension. They are thus possible to capture and analyze through micro-data points of discourse at every turn of a group member's speech and can act as signals for "trigger events," thereby offering a lens through which patterns, sequences, and models in SSRL can be traced and examined (Järvelä, Nguyen, & Hadwin, 2023). The first coding scheme for regulatory characteristics follows a method from prior studies (Näykki et al., 2021; Nguyen et al., 2023) for classifying interaction processes for regulation as *metacognitive, cognitive, socio-emotional,* and *task execution* interactions (see Appendix 1). The data were then coded by a researcher, which included 2,125 utterances with different regulatory characteristics defined in total. A reliability test of the coding was done with two coders for 239 utterances resulting in moderate to high Cohen's Kappa value (κTask execution= 0.63; κCognitive = 0.69; κMetacognitive = 0.71; κSocio-emo = 0.88).

For the secondary coding scheme, given this paper's pioneering attempt to examine the deliberative characteristics within SSRL at a granular level, no pre-existing coding framework was found suitable. Therefore, we adopted the constant comparison method from Onwuegbuzie et al. (2009), initiating it with an open coding phase, and iteratively refining the descriptors into themes. In total, we identified 11 different micro-level processes used by groups to deliberate for SSRL within the collaborative task (see Appendix 2). Despite its inductive nature, these labels were developed in consistent alignment with SSRL theory from Järvelä et al. (2018), focusing on the deliberate negotiation mechanism of SSRL adaptation. Cohen's kappa score of κ = 0.76 for the deliberative characteristics coding scheme affirms a reliability of moderate to high levels.

3.2.2. Layer 2: Sequence Analysis

After the initial pre-processing and analysis, temporal sequence analysis is applied to examine the similarity of groups' deliberative interactions to detect patterns. First, 2,125 turns of transcribed discourse interactions, coded for regulatory and deliberative characteristics, were transformed into 43 three-minute sequences. One overly long sequence (141 turns vs. an average of 77) was treated as an outliner and excluded from the analysis, resulting in a total of 42 sequences with 1,984 codes. Next, the optimal matching (OM) algorithm was used to calculate and compare 42 sequences to evaluate their similarity or distance from each other based on their code for deliberative characteristics. In particular, the OM algorithm uses the Levenshtein distance to measure the minimal cost of transforming one sequence into another, based on operations such as insertion, deletion, or substitution (Abbott & Tsay, 2000). This was implemented using Python programming language with the *scikit-learn* library (Pedregosa et al., 2018). The optimal cluster number was determined using a combination of the goodness-of-fit Silhouette coefficient score, the dendrogram, and the interpretability of the clusters.

3.2.3. Layer 3: Deliberation Patterns Analysis

Within Layer 3, three analytical methods were used to reveal the quantitative, structural, and sequential characteristics of different deliberative patterns identified in Layer 2, as well as their relationship with group interactions for regulation. First, from a quantitative perspective, descriptive analysis was used to analyze the frequency of different interactions for regulation and interactions for deliberation within each cluster type. Chi-square and Cramer V tests were used to identify significant differences between clusters in these characteristics.

Second, from a structural perspective, epistemic network analysis (ENA) was performed to unveil the interconnections between activity patterns related to deliberative and regulatory characteristics across clusters. ENA is a sophisticated modelling technique adept at capturing, visualizing, and quantitatively comparing the structural relationship of different learning activities (Rakovic et al., 2023). This method operates under three assumptions: 1) meaningful features in the data, referred to as Codes, can be systematically identified; 2) the data is organized into local structures, such as conversations; and 3) a crucial aspect of the data is the way these Codes are interconnected within conversations (Bowman et al., 2021; Williamson Shaffer, 2017). By identifying and quantifying connections among elements in coded data, ENA creates a weighted network that models these interactions across different group sequences (Swiecki & Williamson Shaffer, 2020). Its relevance in our study is highlighted by its ability to comprehensively model the temporal co-occurrences of interactions across groups, for both regulatory and deliberative characteristics—even within our smaller dataset. Our study uses an ENA Webkit (epistemicnetwork.org) to perform the analysis and its visualization.

Third, from a sequential perspective, a process-driven analysis is used to identify and characterize the sequences and underlying constructs of regulatory and deliberative characteristics between clusters. The analysis was performed using Fluxicon Disco, a frequently embraced process mining software in learning sciences research for describing sequences in learning logs or activities (e.g., Malmberg et al., 2017; Nazeri et al., 2023). Process mining uses algorithms to analyze and identify process models (i.e., the dominant process flows) from event data (i.e., recorded logged data or coded events from verbal or behaviour protocols). It takes into account all events to generate a comprehensive process model, facilitating the analysis of the relative sequence and arrangement of these events (Sonnenberg & Bannert, 2019). As such, this method is particularly relevant in the context of regulated learning to capture the temporal and sequential nature of the specific interactions for deliberation that draw out the control processes of regulation.

4. Results and Findings

4.1. RQ1: What Type of Group Deliberative Characteristics Are Manifested in Response to Different Regulation Triggering Events?

4.1.1. Two Types of Deliberation Sequences Through Different Regulatory Triggers

The first set of questions aimed to identify the type of deliberative characteristics manifested in response to regulatory triggering events. After Layer 1 of pre-processing and analysis, 1,894 turns of transcribed discourse interactions were coded for deliberative characteristics and transformed into 42 three-minute sequences. The optimal clustering results generated from Layer 2 reveal two types of deliberative characteristics. Figure 3(a) illustrates the AHC results of a hierarchical tree cluster of deliberation sequences. Type 1 consists of 15 sequences and Type 2 consists of 27 sequences. The descriptive statistic in Table 1 can be interpreted as follows: generally, interactions in Type 1 are evenly distributed between Cognitive, Metacognitive, and Task execution (approximately 30% each), and only 0–6% for Socio-emotional interaction. Meanwhile, Type 2 shows higher engagement in Metacognitive interactions ($M = 0.43$, $SD = 0.5$) compared to Type 1 ($M = 0.32$, $SD = 0.47$), and correspondingly, less engagement in Cognitive and Task execution.

Table 1. Proportion of Group Interactions for Regulation per Cluster Type

	Regulatory Dimension								
	Total talk/n	Cognitiv		Metacognitive		Socio-emo		Task execution	
	f	M	SD	M	SD	M	SD	M	SD
Cluster1_PIA	975	.31	.46	.32	.47	.06	.24	.31	.46
D1G1	181	.23	.42	.32	.47	.08	.28	.37	.48
D2G1	126	.15	.36	.35	.48	.14	.35	.36	.48
D3G1	273	.47	.50	.32	.47	.02	.13	.19	.40
D5G1	217	.22	.42	.30	.46	.06	.25	.41	.49
D6G1	58	.50	.50	.34	.48	.10	.31	.05	.22
SD3G1	57	.16	.37	.39	.49	.00	.00	.46	.50
SD4G1	63	.37	.49	.32	.47	.03	.18	.29	.46
Cluster2_TFA	1,009	.26	.44	.43	.50	.04	.20	.27	.44
D1G1	89	.34	.48	.55	.50	.01	.11	.10	.30
D2G1	58	.24	.43	.45	.50	.07	.26	.24	.43
D4G1	119	.16	.37	.44	.50	.02	.13	.39	.49
D5G1	24	.00	.00	.79	.41	.21	.41	.00	.00
D6G1	157	.31	.46	.32	.47	.06	.23	.31	.46
SD1G1	127	.35	.48	.46	.50	.05	.21	.15	.36
SD2G1	152	.33	.47	.28	.45	.03	.18	.36	.48
SD3G1	161	.21	.40	.42	.50	.04	.20	.33	.47
SD41G1	122	.20	.40	.59	.49	.01	.09	.20	.41

Note: The letters in the first column represent student groups, where D and SD indicate the day of the experiment, and G indicates the group number.

According to Figure 3(b), both types exhibit similar frequency across various deliberative states in terms of percentage. Nonetheless, Type 1 shows a higher frequency than Type 2 of the following states: "Define the problem," "Establish strategy," "Agree and implement," and "Generate options." Type 2 is more prevalent in "Attempting ideas," "Monitoring" and

"Evaluating." The Chi-square test for both deliberative and regulatory dimensions of interactions revealed significant differences in the proportions associated with each type. Specifically, the deliberative dimension yielded a significant result ($\chi 2 = 131.9$; df = 10; $p < .001$) with a medium effect size (V = 0.26; df = 1). The regulatory dimension showed a significant result ($\chi 2 = 26.8$; df = 3; $p < .001$) with a small effect size (V = 0.12; df = 1). We thus conclude that there are distinct regulatory and deliberative characteristic patterns between the two types.

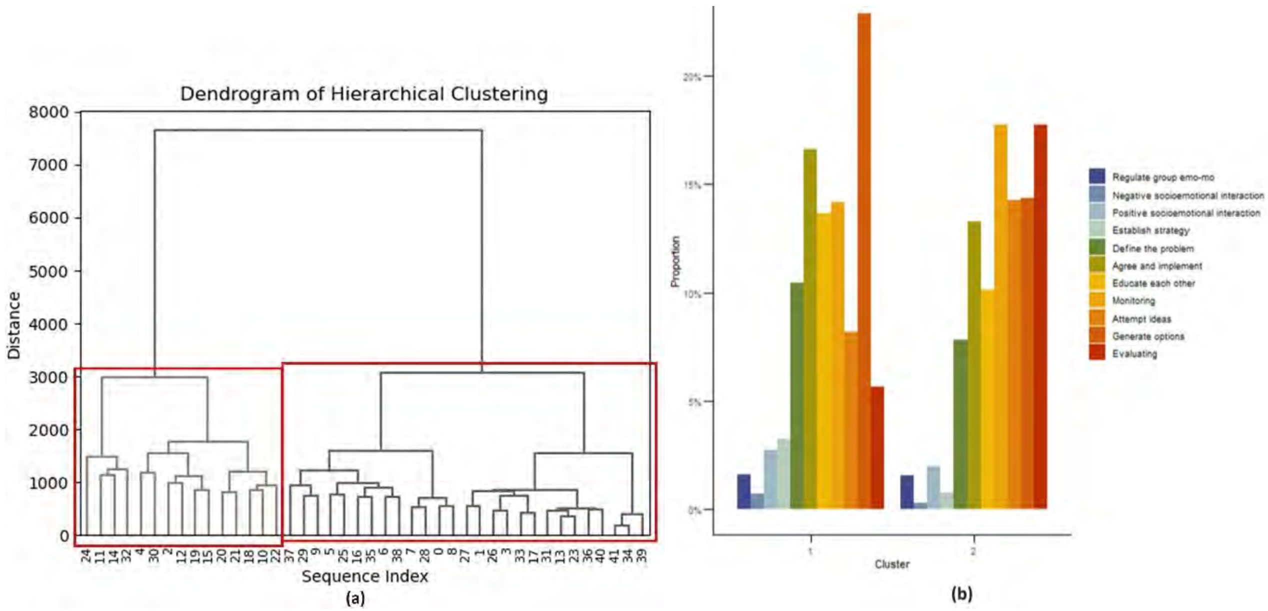

Figure 3. Ward's clustering result for 42 deliberation sequences. Note: Type 1 = left area; Type 2 = right area.

4.1.2. The Difference in the Structural Characteristics of the Two Types of Deliberation Sequences

Turning now to structural examination, the regulatory and deliberative characteristics were defined by a representation that demonstrates the network values and the positions of the square centroid (i.e., mean) for each type in the ENA plots (see Figure 4). In the figure, coloured dots represent individual students, while grey dots represent types of interactions related to regulation (Figure 4a) and deliberation (Figure 4b). The size and edges of dots reflect the relative frequency of co-occurrence or connection between two codes.

First, Figure 4(a) reveals a similar regulatory characteristic structure between Type 1 and Type 2, using Cognitive, Metacognitive, Task execution, and Socio-emotional nodes. The Socio-emotional dimension was weakly associated with other nodes in both types. Despite no Y-axis differences, X-axis comparisons showed significant divergence in mean centroid values between the types, as shown by the Mann-Whitney test results (MdnType 1 = -0.25, MdnType 2 = -0.04, U = 1150.00, $p < .001$, r = 0.34). This difference is also highlighted in the subtraction network of Figure 4(a) indicating that Type 1 has a stronger connection between these dimensions, particularly Cognition and Task execution. However, without the subtraction model, the differentiation in terms of the regulatory structure between Type 1 and Type 2 might be challenging to interpret, as they share considerable similarities in the ENA representation. In anticipation of this challenge, an additional, more refined lens of deliberative interactions is adopted to provide further insights into the structural difference in group interactions between these two types.

In Figure 4(b), a clear difference in deliberative characteristics was identified between the two types. This is further highlighted by the respective locations of the most weighted region, shown as red circles in Figure 4(b). For Type 1, this region of the ENA was situated at the lower right corner, focusing on "Establish strategy," "Educate each other," "Agree and implement" and "Monitoring." Meanwhile, Type 2 leaned toward the outer left corner of the epistemic network, with a more spread-out connection among all deliberation nodes. However, there was a subtle emphasis on "Agree and implement," "Attempt ideas" and especially "Evaluating" and "Monitoring." Although there was no statistical difference observed for the Y-axis, the Mann-Whitney test showed that the mean square centroid of Type 1 (MdnType 1 = -0.26) is significantly different from Type 2 (MdnType 2 = -0.03, U = 550.00, $p < .001$, r = 0.68).

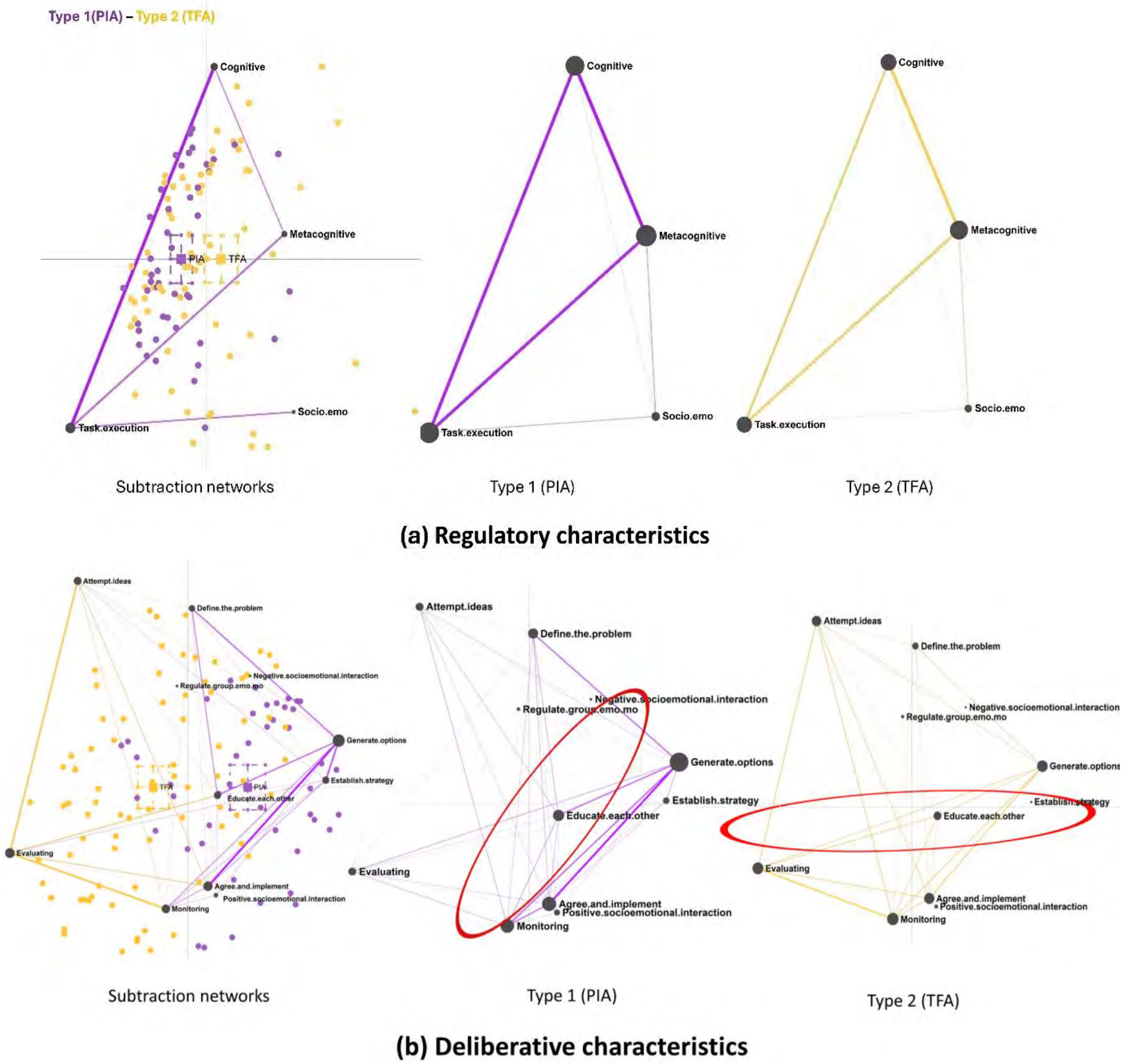

Figure 4. Ward's clustering result for 42 deliberation sequences. Note: Type 1 = left area; Type 2 = right area.

4.1.3. Illustrative Examples

To learn more about the characteristics of these types, we revisited video data for sequences in each clustering group. We observed Type 1 groups typically started by identifying an issue (metacognitive), discussing information (cognitive), and then creating solutions, demonstrating a balanced approach to task execution, awareness, and deliberation, labelled as the Plan and Implementation Approach (PIA) type (Figure 5). In contrast, Type 2 groups focused on defining problems (metacognitive) and directly experimenting with solutions, often skipping in-depth problem analysis, leading to a pattern of trial and error, termed the Trials and Failures Approach (TFA), illustrated in Figure 6.

Figure 5. Example of Type 1 (PIA).

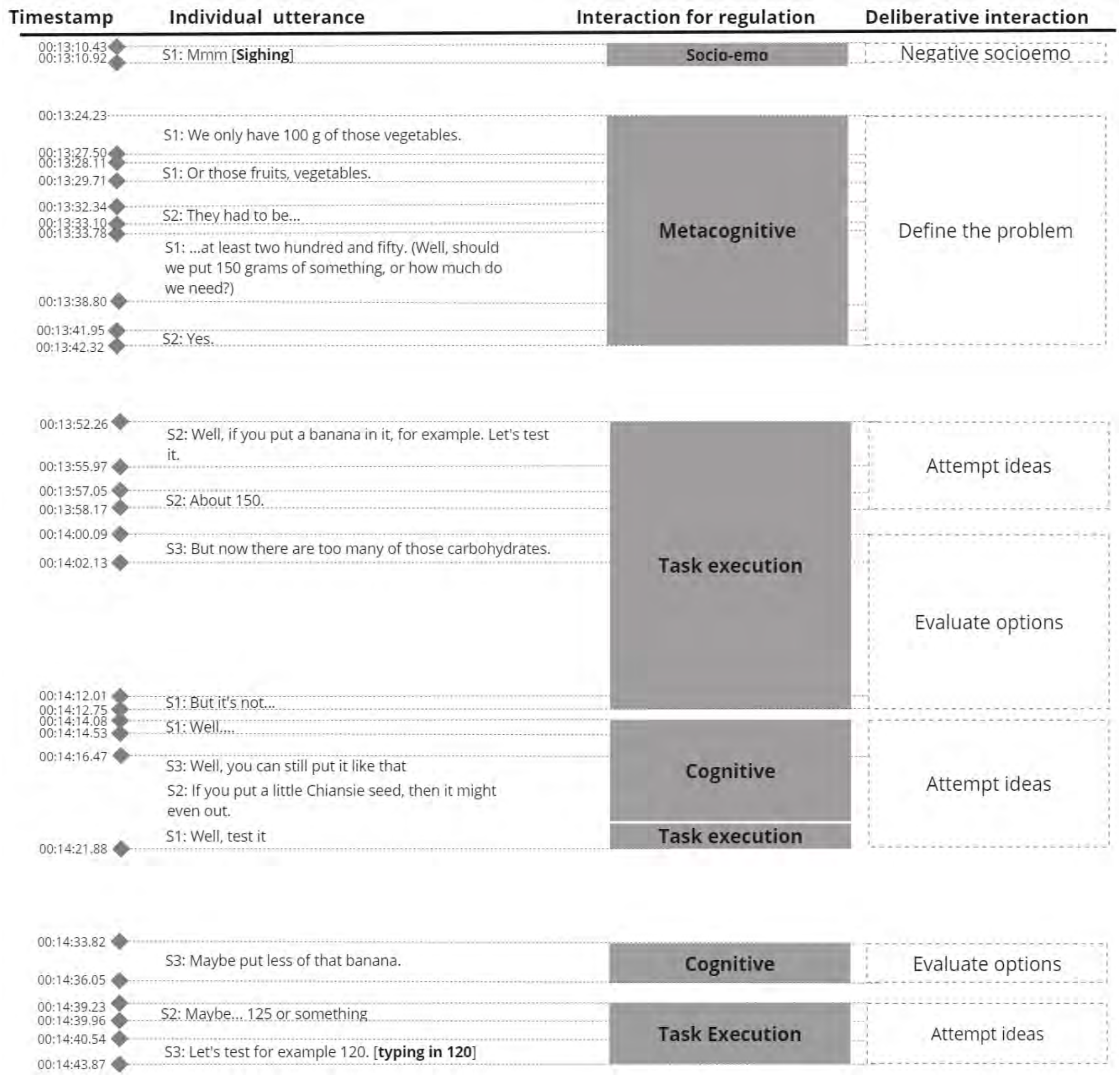

Figure 6. Example of Type 2 (TFA).

4.2. RQ2. What Are the Patterns of Group Deliberative Characteristics in Response to Different Regulation Triggering Events in Collaborative Learning Tasks?

To answer RQ2, we employed process-mining analysis to reveal the most dominant trajectory of regulatory (see Figure 7) and deliberative characteristics (see Figure 8) of both PIA and TFA types. The maps reported the pathway with absolute frequencies and case coverages in the percentage of interactions while the shifting patterns between these two clusters of groups through separate phases of the triggering events are illustrated in Figure 9.

Overall, both types exhibit a strong emphasis on the dynamic recurrent shift between cognitive, metacognitive, and task execution. The process maps not only affirm the findings from the ENA but also reveal the sequential unfolding of these regulatory characteristic patterns. In the PIA type, groups were more likely to engage in *cognitive interaction* (f = 358) repeatedly, which then led to *task execution* ($f_{\text{Cognitive} \rightarrow \text{Task execution}}$ = 100%) and looped back. This Type's engagement in *metacognitive interaction*, though less than that of the TFA type, seems to function as a specialized loop that reciprocally interacts with *cognitive interactions* ($f_{\text{Metacognitive} \rightarrow \text{Cognitive}}$ = 89%, $f_{\text{Cognitive} \rightarrow \text{Metacognitive}}$ = 68%). The TFA type, on the contrary, is most prevalent in its engagement with repeated loops of metacognitive interactions ($f = 469$, $f_{\text{Metacognitive} \rightarrow \text{Metacognitive}} = 100\%$), a pattern not observed in PIA groups. Nonetheless, at higher abstract level of SSRL, the PIA pattern might appear to share similarities to the TFA and can make it challenging to affirmatively conclude these interpretations. Process maps in Figure 8 offer a detailed view into the deliberative mechanisms distinguishing the two types of regulatory characteristics.

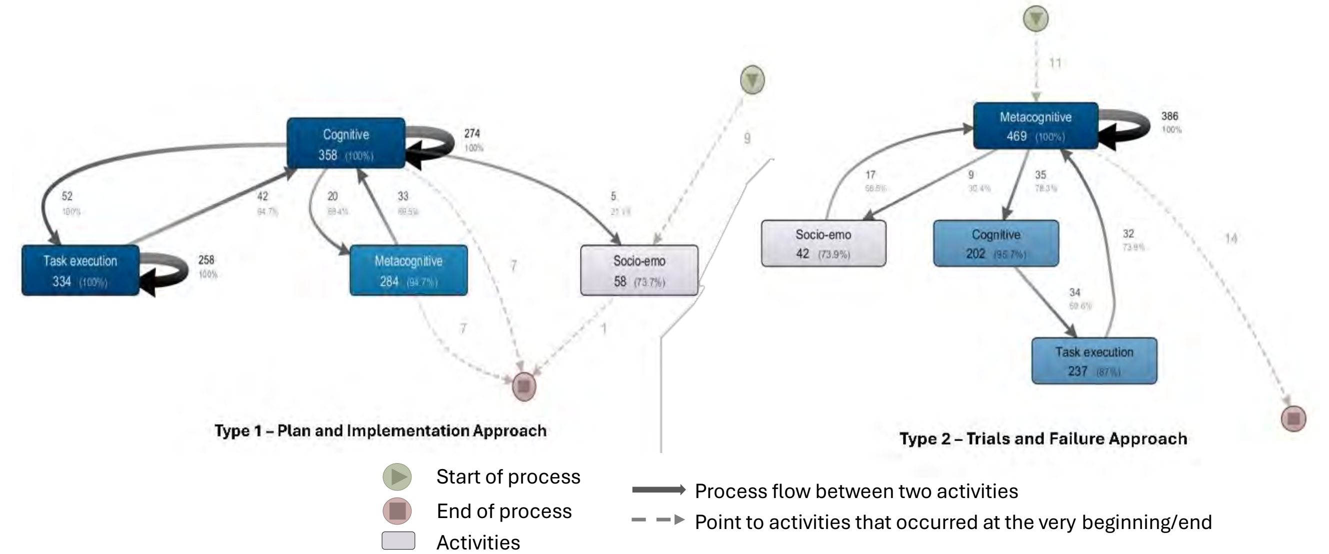

Figure 7. Process map for patterns of interactions for regulation of PIA and TFA type.

Figure 8 indicates that the deliberative interactions of Type 1, the PIA, reflect a more intertwined and iterative characteristic than that of Type 2, the TFA. The PIA often start by engaging with *positive socioemotional interaction* before *generating options* ($f = 223$) and exhibits a higher proportion of reaching agreement and implementing their generated options ($f_{\text{Generate options} \rightarrow \text{Agree and implement}} = 60\%$) than that of the TFA type ($f_{\text{Generate options} \rightarrow \text{Agree and implement}} = 55\%$). In both PIA and TFA, the *define the problem* interactions often leads to *educate each other* and *attempt ideas*. However, the PIA type follows this with a smaller cycle of *monitoring* → *evaluating* → *establish strategy*, which reinforces the bigger cyclical process of *generating options* → *agree and implement* → *define the problem*. This pattern indicates that PIA reflects a more strategic approach to problem-solving and task execution, requiring less engagement in the actions of randomly testing ideas ($f_{\text{PIA's } \textit{Attempt ideas}} = 80$, $f_{\text{TFA's } \textit{Attempt ideas}} = 144$). This type of ideas generation, either for the task or for the problem, is a result of well-informed reasoning, deliberation, and consensus decision. Furthermore, PIA demonstrates a more adaptive pattern, since even when attempting ideas, they follow with monitoring and reflection before negotiating, agreeing, and implementing necessary changes.

The TFA type, on the contrary, often jumps back and forth between *evaluating* ($f_{\text{Attempt ideas} \rightarrow \text{Evaluating}} = 41\%$) and *generate options* ($f_{\text{Evaluating} \rightarrow \text{Generate options}} = 26\%$). This further reinforces the cycles of *monitoring* → *generate options* or *monitoring* → *define the problem* → *generate options* and further testing out other ideas. This pattern, marked by a lack of strategic problem-solving ($f_{\text{PIA's } \textit{Establish strategy}} = 32$, $f_{\text{TFA's } \textit{Establish strategy}} = 8$) and random idea attempts, also reflects a maladaptive pattern of regulation. The evaluation of TFA attempt ideas only raises the metacognitive awareness of negative signals but fails to result in proper planning and adjustment, as demonstrated in further *attempts ideas* interactions.

Figure 9 illustrates the distribution of sequences and shifting patterns between the two cluster types for each group. According to this result, most groups (f = 80%) display a consistent pattern in their deliberation sequences, exclusively or almost exclusively adhering to either Type 1 (f = 30%) or Type 2 (f = 50%). The remaining groups (f = 20%) show a more dynamic pattern, with their deliberation sequences alternating between two types at various stages of cognitive and emotional regulation triggering events. This result may reflect that most learners lack a more varied and strategic repertoire of collaboration and regulation skills necessary for effectively addressing the situational needs and challenges (fTFA = 27, fPIA = 15). In most cases, they adhere to their existing type of deliberation sequence and do not alter it in response to regulatory triggers. These results corroborate previous research that found that students often ignore or fail to recognize and respond to emerging needs or situations that require regulation (Järvelä & Bannert, 2021; Nguyen et al., 2023).

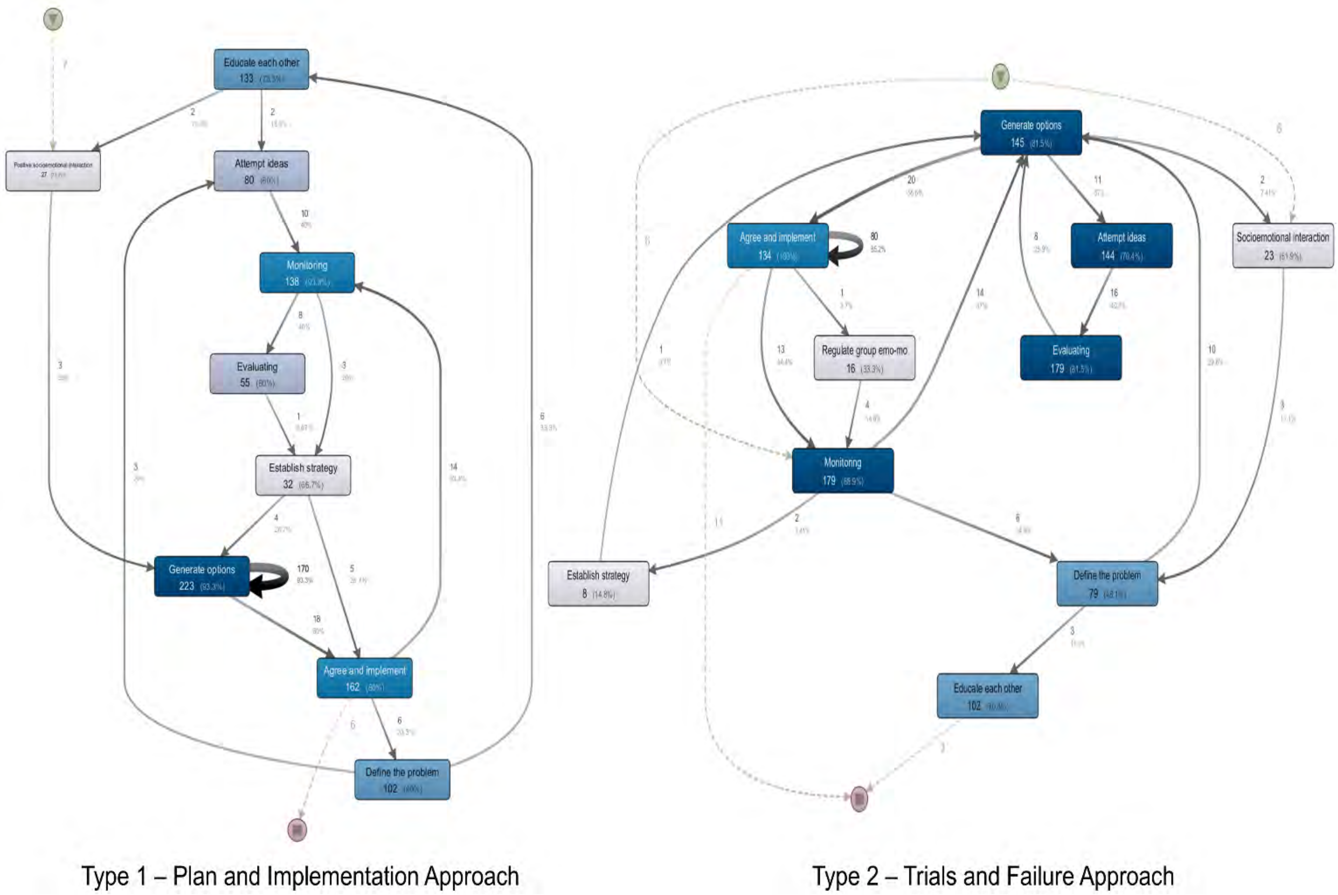

Figure 8. Process map for deliberation patterns of PIA and TFA type.

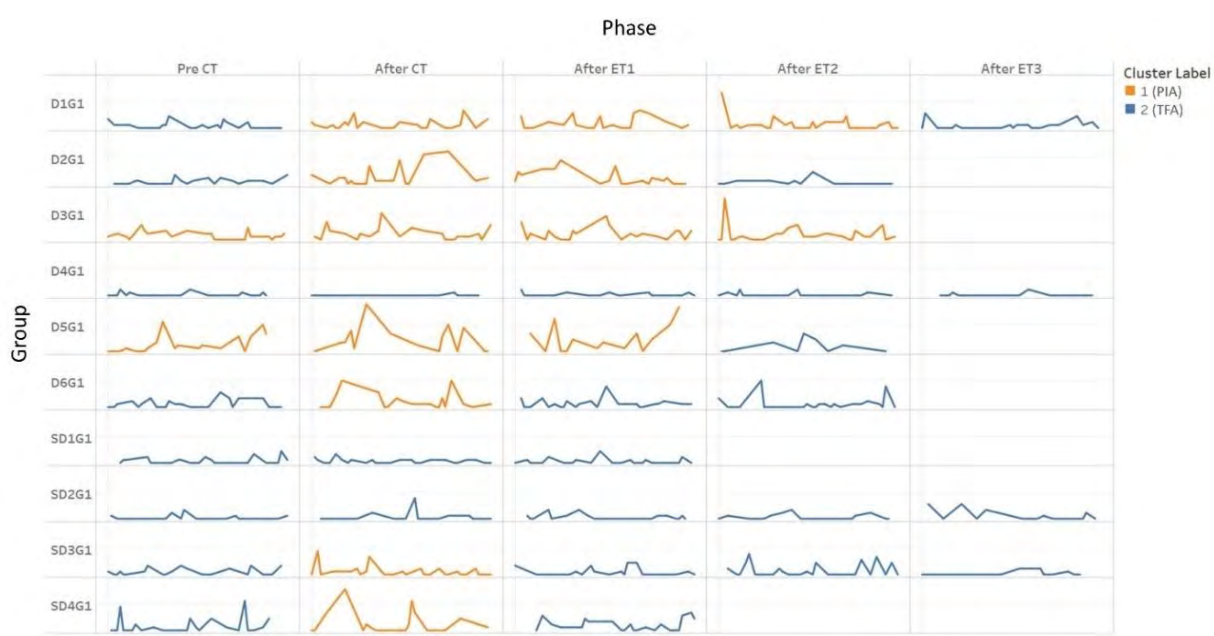

Figure 9. Distribution of the PIA and TFA sequence types across groups and phases

5. Discussion and Implications

This study aims to enhance the theoretical understanding of SSRL by introducing a micro-lens of deliberation for interactions inviting for SSRL and applying a three-layered analysis integrating LA/AI-enabled methods. Our proposed approach also addresses the challenges associated with the operationalization of SSRL.

5.1. Theoretical Contributions to Understanding Deliberation in SSRL

Whilst previous research has only suggested the relationship between adaptive and maladaptive behaviour with regulation (Malmberg et al., 2017; Sobocinski et al., 2020), the temporal characteristic of this pattern remains largely qualitative and descriptive. Our study offers process models of the specific behavioural sequences related to deliberation underpinning these regulatory responses in CL. We identify two deliberation patterns: the Plan and Implementation Approach (PIA), reflecting adaptive regulatory behaviour with a balanced interplay of cognitive, metacognitive, and task execution interactions; and the Trials and Failure Approach (TFA), reflecting a maladaptive behaviour with a stronger focus on reactive metacognitive interactions. Our findings also point to a mirrored alignment in the regulatory and deliberative characteristics of each type, corroborating the relationship established by previous research (Dang, Vitiello, et al., 2023). Nonetheless, this study goes further by shedding light on the complex characteristics of these two types, examining their quantitative frequency, structural composition, and sequential aspects. Researchers argue that successful regulated learners are identified by their ability to overcome situation-specific challenges with responses that fit the task demands (Bakhtiar & Hadwin, 2020). By examining learner responses to challenging triggering events, our findings reveal critical features of strategic action sequences that are more adaptive (PIA) and those that are not (TFA) for learning and SSRL. Overall, this contributes to a deeper understanding of the mechanisms underpinning SSRL and further argues for the role of using deliberation as a new lens to understand and model this complex phenomenon.

Furthermore, our study also extends a recent discussion on leveraging and combining observation and analysis capabilities of AI-driven techniques to refine and reinforce the advancement of the theoretical landscape of SSRL and collaborative learning. Before this study, the appearance of metacognitive activities was largely associated with regulation (Isohätälä et al., 2017; Malmberg et al., 2017) or identified as an indicator of regulation in CL (Järvelä, Nguyen, Vuorenmaa, et al., 2023). Our finding contests the conventional perspective that metacognitive activities directly equate to effective regulation, positing instead that metacognitive processes, particularly when unaccompanied by strategic analysis and planning, as observed in the TFA pattern, may lead to counterproductive outcomes. The key difference between adaptive and maladaptive regulation is not just the frequency of metacognitive activities; it also depends on the quality and sequence of metacognitive interactions that frame the episode. This is in line with previous research indicating that the metacognitive process of regulation varies depending on several fundamental factors (e.g., conditions, events, and specificity of the mechanism; Greene & Azevedo, 2009). This level of granularity can only be captured through adding a more refined lens, such as deliberation, facilitated by the advanced statistical and computational power of AI-driven techniques. Overall, our findings highlighted the complex nature of SSRL and the pivotal role that deliberative interactions and innovative LA/AI technologies play in challenging our comprehension of the field. Both these aspects further argue for the approach demonstrated in our study and open opportunities for future research.

5.2. Methodological Contributions to Multimodal Learning Analytics for SSRL Research

Our study also fills a current methodological gap in the field related to the operationalization of SSRL (Cress et al., 2021; Giannakos & Cukurova, 2023). The complexity of SSRL necessitates a comprehensive approach of multimodal data triangulation and LA/AI techniques (Järvelä & Bannert, 2021; Winne, 2022). However, due to the substantial resources required for in-depth analysis and micro-analytical recording of rich qualitative data, most studies in SSRL must compromise at a more macro granularity. It has been argued that this often results in datasets that are constrained in 1) their ability to be fully synthesized with data of other modalities, 2) their suitability for machine learning applications, and 3) the depth of temporal insights into these processes (Nguyen et al., 2022). This research collects video recordings and proposes a human–AI collaboration of a three-layered analysis integrating LA/AI-enabled methods to investigate group-level interaction patterns in response to regulatory triggers. Compared to previous studies, this approach proposes an additional fine-grained lens of deliberation alongside SSRL. This analytical approach allows for the tracing, evaluating, and understanding of the complex nature of this phenomenon. This new lens not only advances SSRL theory but more importantly also aligns with the operationalization of sophisticated analysis and machine-learned models. AI-driven techniques are integrated for the efficient automated, multilayered analysis of qualitative data from video. Furthermore, the micro level of this deliberation lens offers a versatile data foundation of discourse interactions that can be easily synthesized with different data streams for multimodal analysis. By allowing a new theoretical lens of different granularities that can be well connected with other modalities and sophisticated analytical approaches, this study responds to the current call for using LA/AI to push the boundaries of established understanding in SSRL (Chen et al., 2020; Giannakos & Cukurova, 2023). Our study lays the groundwork for future empirical SSRL research employing similar methodologies.

5.3. Potential Practical Implications for Different Educational Stakeholders

Our findings offer practical implications for capturing and supporting SSRL in different collaborative contexts. While Dang, Vitiello et al.'s (2023) work has identified an immediate shift towards the metacognitive in group behaviour after triggering events, our findings further revealed a general stability in group deliberative patterns across time. This suggests that such shifts might only be temporary, with groups often reverting to their default deliberative patterns even when situational demands change. This observation not only aligns with but also amplifies existing literature that characterizes regulatory cycles as a series of iterative adaptations across different temporal proximities (Järvelä & Bannert, 2021; Nguyen, 2025). For education practitioners and researchers, this emphasizes the need for interventions to address both the immediate, situated adaptations but also the longer-term development of (S)SRL skills. Specifically, this means that providing feedback on current student practices, prompting and guiding them to accurately account for their performance patterns, and teaching effective collaboration and adaptation strategies beforehand are crucial for enabling students to shift their patterns in the future. In this vein, our identification of two distinct deliberative patterns — PIA and TFA — provides a means (i.e., learner-specific action sequences) to model adaptive and maladaptive regulatory cycles. For developers and researchers in AIED, these specific action sequences illustrating productive (PIA) and unproductive (TFA) behaviours can be used to design automated interaction analytic tools that provide interventions and feedback in real-world learning environments. This has far-reaching implications for the design of intelligent tutoring systems and other educational technologies aimed at fostering adaptive learning environments.

5.4. Limitations

This study has certain limitations. First, the research was conducted in a controlled laboratory environment, which may not fully reflect complexities in real world CL scenarios. Second, the sample size was small, with a limited range of demographic backgrounds. This limits the generalizability of the findings. Therefore, future research needs to expand the scope by employing larger sample sizes and by situating experiments in less controlled, more complex learning environments. Additionally, as the primary focus of this study was on exploring group-level deliberation, we only utilized video data for deliberative and regulatory discourse interactions. Subsequent research can further exploit this perspective in integration with other data modalities (e.g., eye tracking, physiological, facial expression) and delve into the impact of other variables, such as individual emotional states, motivational factors, and individual mental models on the manifestation of group deliberation for SSRL.

6. Conclusion

Our study stands as a pioneering attempt to illuminate these unexplored areas by utilizing AI models as analytical tools, propose deliberative interactions as a new micro-level lens, and draw upon the literature on (S)SRL (Järvelä, Nguyen, & Hadwin, 2023; Winne & Hadwin, 1998). Previous research in learning sciences has posited that deliberate negotiation is a crucial mechanism for SSRL and collaborative success (Hadwin et al., 2018; Järvelä et al., 2018) but have not yet explained how this process unfolds in collaborative learning and its relationship with SSRL. Through this human–AI collaborative approach, our study responds to the current call to bridge the gap between LA and AI and learning theories, and contributes to both the theoretical and methodological landscapes of learning sciences, especially SSRL. Our empirical findings verify that the coding scheme for deliberation, the SSRL triggering framework, and the method proposed here can indeed be valuable for exploring SSRL from this perspective. It serves as a blueprint for future research in SSRL, aiming to leverage multimodal data and advanced analysis through LA/AI, leading to significant theoretical, analytical, and practical implications.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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References

Abbott, A., & Tsay, A. (2000). Sequence analysis and optimal matching methods in sociology: Review and prospect. *Sociological Methods & Research*, *29*(1), 3–33. https://doi.org/10.1177/0049124100029001001

Andrade, A., Delandshere, G., & Danish, J. A. (2016). Using multimodal learning analytics to model student behavior: A systematic analysis of epistemological framing. *Journal of Learning Analytics*, *3*(2), 282–306. https://doi.org/10.18608/jla.2016.32.14

Bakhtiar, A., & Hadwin, A. (2020). Dynamic interplay between modes of regulation during motivationally challenging episodes in collaboration. *Frontline Learning Research*, *8*(2), 1–34. https://doi.org/10.14786/flr.v8i2.561

Bowman, D., Swiecki, Z., Cai, Z., Wang, Y., Eagan, B., Linderoth, J., & Williamson Shaffer, D. (2021). The mathematical foundations of epistemic network analysis. In A. R. Ruis & S. B. Lee (Eds.), *Advances in quantitative ethnography: Second international conference, ICQE 2020, Malibu, CA, USA, February 1–3, 2021, Proceedings* (pp. 91–105). Springer Cham. https://doi.org/10.1007/978-3-030-67788-6_7

Chen, X., Xie, H., Zou, D., & Hwang, G.-J. (2020). Application and theory gaps during the rise of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, *1*, 100002. https://doi.org/10.1016/j.caeai.2020.100002

Cress, U., Rosé, C., Wise, A. F., & Oshima, J. (Eds.). (2021). *International handbook of computer-supported collaborative learning*. Springer.

Cukurova, M., Giannakos, M., & Martinez-Maldonado, R. (2020). The promise and challenges of multimodal learning analytics. *British Journal of Educational Technology*, *51*(5), 1441–1449. https://doi.org/10.1111/bjet.13015

Cukurova, M., Kent, C., & Luckin, R. (2019). Artificial intelligence and multimodal data in the service of human decision-making: A case study in debate tutoring. *British Journal of Educational Technology*, *50*(6), 3032–3046. https://doi.org/10.1111/bjet.12829

Dang, B., Nguyen, A., Hong, Y., Nguyen, B.-P. T., & Tran, B.-N. D. (2023). Revealing the hidden structure of affective states during emotion regulation in synchronous online collaborative learning. *Proceedings of the 56th Hawaii International Conference on System Sciences* (HICSS-56), 3–6 January 2023, Lahaina, HI, USA (pp. 14–23). ScholarSpace. https://hdl.handle.net/10125/102632

Dang, B., Vitiello, R., Nguyen, A., Rosé, C. P., & Järvelä, S. (2023). How do students deliberate for socially shared regulation in collaborative learning? A process-oriented approach. In C. Damşa, M. Borge, E. Koh, & M. Worsley (Eds.), *Proceedings of the 16th International Conference on Computer-Supported Collaborative Learning* (CSCL 2023), 10–15 June 2023, Montréal, QC, Canada (pp. 59–66). International Society of the Learning Sciences. https://repository.isls.org//handle/1/9265

Dawson, S., Joksimovic, S., Poquet, O., & Siemens, G. (2019). Increasing the impact of learning analytics. *Proceedings of the 9th International Conference on Learning Analytics & Knowledge* (LAK '19), 4–8 March 2019, Tempe, AZ, USA (pp. 446–455). ACM Press. https://doi.org/10.1145/3303772.3303784

Gelfand, M. J., Harrington, J. R., & Leslie, L. M. (2014). Conflict cultures: A new frontier for conflict management research and practice. In O. B. Ayoko, N. M. Ashkanasy, & K. A. Jehn (Eds.), *Handbook of conflict management research* (pp. 109–135). Edward Elgar.

Giannakos, M., & Cukurova, M. (2023). The role of learning theory in multimodal learning analytics. *British Journal of Educational Technology*, *54*(5), 1246–1267. https://doi.org/10.1111/bjet.13320

Greene, J. A., & Azevedo, R. (2009). A macro-level analysis of SRL processes and their relations to the acquisition of a sophisticated mental model of a complex system. *Contemporary Educational Psychology*, *34*(1), 18–29. https://doi.org/10.1016/j.cedpsych.2008.05.006

Hadwin, A., Järvelä, S., & Miller, M. (2018). Self-regulation, co-regulation, and shared regulation in collaborative learning environments. In D. H. Schunk & J. A. Greene (Eds.), *Handbook of self-regulation of learning and performance* (2nd ed., pp. 83–106). Routledge.

Hurme, T.-R., Järvelä, S., Merenluoto, K., & Salonen, P. (2015). What makes metacognition as socially shared in mathematical problem solving? In A. Peña-Ayala (Ed.), *Metacognition: Fundaments, applications, and trends: A profile of the current state-of-the-art* (pp. 259–276). Springer Cham. https://doi.org/10.1007/978-3-319-11062-2_10

Ihnen, C. (2014). Negotiation and deliberation: Grasping the difference. *Argumentation*, *30*, 1–21. https://doi.org/10.1007/s10503-014-9343-1

Isohätälä, J., Järvenoja, H., & Järvelä, S. (2017). Socially shared regulation of learning and participation in social interaction in collaborative learning. *International Journal of Educational Research*, *81*, 11–24. https://doi.org/10.1016/j.ijer.2016.10.006

Järvelä, S., & Bannert, M. (2021). Temporal and adaptive processes of regulated learning: What can multimodal data tell? *Learning and Instruction*, *72*, 101268. https://doi.org/10.1016/j.learninstruc.2019.101268

Järvelä, S., Hadwin, A., Malmberg, J., & Miller, M. (2018). Contemporary perspectives of regulated learning in collaboration. In F. Fischer, C. E. Hmelo-Silver, S. R. Goldman, & P. Reimann (Eds.), *International handbook of the learning sciences* (pp. 127–136). Routledge. https://doi.org/10.4324/9781315617572-13

Järvelä, S., Nguyen, A., & Hadwin, A. (2023). Human and artificial intelligence collaboration for socially shared regulation in learning. *British Journal of Educational Technology*, *54*(5), 1057–1076. https://doi.org/10.1111/bjet.13325

Järvelä, S., Nguyen, A., Vuorenmaa, E., Malmberg, J., & Järvenoja, H. (2023). Predicting regulatory activities for socially shared regulation to optimize collaborative learning. *Computers in Human Behavior*, *144*, 107737. https://doi.org/10.1016/j.chb.2023.107737

Järvenoja, H., Järvelä, S., & Malmberg, J. (2020). Supporting groups' emotion and motivation regulation during collaborative learning. *Learning and Instruction*, *70*, 101090. https://doi.org/10.1016/j.learninstruc.2017.11.004

Malmberg, J., Järvelä, S., & Järvenoja, H. (2017). Capturing temporal and sequential patterns of self-, co-, and socially shared regulation in the context of collaborative learning. *Contemporary Educational Psychology*, *49*, 160–174. https://doi.org/10.1016/j.cedpsych.2017.01.009

Meier, A., Spada, H., & Rummel, N. (2007). A rating scheme for assessing the quality of computer-supported collaboration processes. *International Journal of Computer-Supported Collaborative Learning*, *2*(1), 63–86. https://doi.org/10.1007/s11412-006-9005-x

Molenaar, I., de Mooij, S., Azevedo, R., Bannert, M., Järvelä, S., & Gašević, D. (2023). Measuring self-regulated learning and the role of AI: Five years of research using multimodal multichannel data. *Computers in Human Behavior*, *139*, 107540. https://doi.org/10.1016/j.chb.2022.107540

Näykki, P., Isohätälä, J., & Järvelä, S. (2021). "You really brought all your feelings out": Scaffolding students to identify the socio-emotional and socio-cognitive challenges in collaborative learning. *Learning, Culture and Social Interaction*, *30*(Part A), 100536. https://doi.org/10.1016/j.lcsi.2021.100536

Nazeri, S., Hatala, M., & Neustaedter, C. (2023). Associations of research questions, analytical techniques, and learning insight in temporal educational research: A systematic mapping study. *Journal of Learning Analytics*, *10*(2), 68–84. https://doi.org/10.18608/jla.2023.7745

Nguyen, A. (2025). Human–AI shared regulation for hybrid intelligence in learning and teaching: Conceptual domain, ontological foundations, propositions, and implications for research. *Proceedings of the 58th Hawaii International Conference on System Sciences* (HICSS-58), 7–10 January 2025, Waikōloa Village, HI, USA. Advance online publication.

Nguyen, A., Gardner, L., & Sheridan, D. (2020). Data analytics in higher education: An integrated view. *Journal of Information Systems Education*, *31*(1), 61–71. http://jise.org/Volume31/n1/JISEv31n1p61.html

Nguyen, A., Järvelä, S., Rosé, C., Järvenoja, H., & Malmberg, J. (2023). Examining socially shared regulation and shared physiological arousal events with multimodal learning analytics. *British Journal of Educational Technology*, *54*(1), 293–312. https://doi.org/10.1111/bjet.13280

Nguyen, A., Järvelä, S., Wang, Y., & Rosé, C. P. (2022). Exploring socially shared regulation with an AI deep learning approach using multimodal data. *Proceedings of the 16th International Conference of the Learning Sciences* (ICLS 2022), 6–10 June 2022, Hiroshima, Japan (pp. 527–534). International Society of the Learning Sciences. https://repository.isls.org//handle/1/8836

Onwuegbuzie, A. J., Dickinson, W. B., Leech, N. L., & Zoran, A. G. (2009). A qualitative framework for collecting and analyzing data in focus group research. *International Journal of Qualitative Methods*, *8*(3), 1–21. https://doi.org/10.1177/160940690900800301

Ouyang, F., Xu, W., & Cukurova, M. (2023). An artificial intelligence-driven learning analytics method to examine the collaborative problem-solving process from the complex adaptive systems perspective. *International Journal of Computer-Supported Collaborative Learning*, *18*(1), 39–66. https://doi.org/10.1007/s11412-023-09387-z

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Müller, A., Nothman, J., Louppe, G., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2018). *Scikit-learn: Machine learning in Python*. arXiv. http://arxiv.org/abs/1201.0490

Rakovic, M., Ahmad Uzir, N., Matcha, W., Eagan, B., Jovanović, J., Williamson Shaffer, D., Pardo, A., & Gašević, D. (2023). Network analytics to unveil links of learning strategies, time management, and academic performance in a flipped classroom. *Journal of Learning Analytics*, *10*(3), 64–86. https://doi.org/10.18608/jla.2023.7843

Sobocinski, M., Järvelä, S., Malmberg, J., Dindar, M., Isosalo, A., & Noponen, K. (2020). How does monitoring set the stage for adaptive regulation or maladaptive behaviour in collaborative learning? *Metacognition and Learning*, *15*(2), 99–127. https://doi.org/10.1007/s11409-020-09224-w

Sonnenberg, C., & Bannert, M. (2019). Using process mining to examine the sustainability of instructional support: How stable are the effects of metacognitive prompting on self-regulatory behavior? *Computers in Human Behavior*, *96*, 259–272. https://doi.org/10.1016/j.chb.2018.06.003

Swiecki, Z., & Williamson Shaffer, D. (2020). iSENS: An integrated approach to combining epistemic and social network analyses. *Proceedings of the 10th International Conference on Learning Analytics & Knowledge* (LAK '20), 23–27 March 2020, Frankfurt, Germany (pp. 305–313). ACM Press. https://doi.org/10.1145/3375462.3375505

Ucan, S., & Webb, M. (2015). Social regulation of learning during collaborative inquiry learning in science: How does it emerge and what are its functions? *International Journal of Science Education*, *37*(15), 2503–2532. https://doi.org/10.1080/09500693.2015.1083634

van den Berg, W., Curseu, P. L., & Meeus, M. T. H. (2014). Emotion regulation and conflict transformation in multi-team systems. *International Journal of Conflict Management*, *25*(2), 171–188. https://doi.org/10.1108/IJCMA-05-2012-0038

Vuorenmaa, E., Järvelä, S., Dindar, M., & Järvenoja, H. (2023). Sequential patterns in social interaction states for regulation in collaborative learning. *Small Group Research*, *54*(4), 512–550. https://doi.org/10.1177/10464964221137524

Walton, D. N. (1998). *The new dialectic: Conversational contexts of argument*. University of Toronto Press.

Williamson Shaffer, D. (2017). *Quantitative ethnography*. Cathcart Press.

Winne, P. H. (2022). Modeling self-regulated learning as learners doing learning science: How trace data and learning analytics help develop skills for self-regulated learning. *Metacognition and Learning*, *17*(3), 773–791. https://doi.org/10.1007/s11409-022-09305-y

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Lawrence Erlbaum Associates Publishers.

Appendix 1. Coding Scheme for Regulatory Characteristics

Categories	Description	Example
Metacognitive interaction	Actions and interactions focus on meta-level mental processes toward the control and monitoring of cognitive and emotional activities (orienting, planning, monitoring, evaluating, and regulating). The connection and reflection are aimed at task-related strategies, group processes or dynamics.	*S1: By the way, I don't use this ingredient page at all, I just put it in there and see what happens.* *S2: If we just keep the ingredients the same, but increase their number in the same ratio, so then those percentages go absolutely nowhere.*
Cognitive interaction	Actions and interactions focus on higher learning-related thinking skills such as understanding, analyzing, reasoning, and evaluating at the object level related to task content.	*S2: Well, here are the others, here are all the chia seeds, hazelnut spread, whey protein powder.* *S1: But here would be pineapple or blueberry, then they would be the kind where there would be very little of everything.*
Socio-emotional interaction	Actions and interactions relevant to the expression of one's emotion in social contexts with a clear negative/positive affect nature (e.g., showing gratitude, joking, disputing).	*S1: Oh, good time, this guy first orders a smoothie, and then tells us to make it again and then complains that it's taking us a long time to make it this. [Express annoyance with group shows shared feeling]*
Task execution interaction	Actions and interactions that primarily focus on carrying out task requirements, and completing the task: i.e., type on the computer, read instruction.	*S1: Yeah, I'll change them to one hundred and twenty-five. [Inform current process]* *S2: One hundred and twenty-five. OK that should be twenty-five then.*

Appendix 2. Coding Scheme for Deliberative Interactions

Categories	Description	Example
Define the problem	Share understanding of the problem, defining the present situation and the desired future to make the current issues problem clearer to group members.	*S1: So, what couldn't be there?* *S2: Natural rubber and milk protein allergy.* *S1: Well, should the natural rubber be that low or…* *S2: Yes, all of them should be low. [..]It's not good when hazelnut spread has natural rubber so high…*
Establish strategy	Suggestion and implementation of specific process steps (approaches, techniques, or methods to process the tasks or to optimize the cognitive process).	*S1: […] we need another 250 kilocalories, half of it.* *S2: Yes, […] And then we'll get increased protein and fat if we only put these […] Let's raise everyone a little, so it won't change these ratios.* *S1 & S3: Yeah. (Okay).*
Educate each other	For back-and-forth discussions of group members trying to work on disagreement and align shared understanding by identifying and sharing understanding, information, interests -- reasons, needs, motivations; etc.	*S1: Well, but you mustn't bring a lot of fat at once.* *S2: We already have a package.* *S3: Let's put something in it.* *S2: We don't have that […] You can't put anything left.*
Generate options	Brainstorm and generate a solution for task-related problem-solving, offer alternatives of choices.	*S1: Where can I get more energy?* *S2: Shall we put that oatmeal in there?*
Evaluating	Make a judgement about different aspect of the collaboration: including the ideas, outcomes, group focus, current progress	*S1: Shall we put kale in there when?* *S2: It sounds a bit strange.* *…* *S1: Now it's good. Wise one about 500 [Complement group's strategy]*
Agree and implement	Confirm shared agreement on the options, ideas, and opinions and carry it out.	*S1: Yeah, I'll change them to one hundred and twenty-five. [Inform current process from previous agreement]*
Attempt ideas	Apply for testing out alternatives/solutions without forethought & discussion between group members.	*S1: I'm going to try a bit of randomness here now, there's a moderate one, so not really*
Monitoring	Observe and check on different aspect of the collaboration: including the time, progress, result, quality of the procedure, environment, and groups conditions.	*S1: There are now four hundred and ninety-eight calories. Isn't it about time?* *S2: I don't think it's the time.* *…* *S1: Oh yeah, isn't it, and it's just a visual glitch of ours that the fat is half of what it should be?*
Regulate group emo-mo	Interactions with the intention of regulating group focus or emotional - motivation about the situation	*S1: Well, it's probably right for us.* *S2: If it's the same for you, then we'll trust it.*
Positive socioemotional interaction	Positive socio-emo interactions without the intention of regulation.	*S1: Well, it's not- (It's my own fault when I forgot my allergy.)* *S2 & S3: Synchronous laughing and agreeing to*
Negative socioemotional interaction	Negative/ neutral socio-emo interactions without the intention of regulation.	*S1: Well, if only we scored something. [All group members non-verbal show a lack of motivation]*