JOURNAL OF LEARNING ANALYTICS

SOLAR SOCIETY for LEARNING ANALYTICS RESEARCH

Volume 9(1), 77–92. https://doi.org/10.18608/jla.2022.7429

How the Monitoring Events of Individual Students Are Associated With Phases of Regulation — A Network Analysis Approach

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Abstract

The current study uses a within-person temporal and sequential analysis to understand individual learning processes as part of collaborative learning. Contemporary perspectives of self-regulated learning acknowledge monitoring as a crucial mechanism for each phase of the regulated learning cycle, but little is known about the function of the monitoring of these phases by individual students in groups and the role of motivation in this process. This study addresses this gap by investigating how monitoring coexists temporally and progresses sequentially during collaborative learning. Twelve high school students participated in an advanced physics course and collaborated in groups of three for twenty 90-minute learning sessions. Each student's monitoring events were first identified from the videotaped sessions and then associated with the regulation phase. In addition, the ways in which students acknowledged each monitoring event were coded. The results showed that cyclical phases of regulation do not coexist. However, when we examined temporal and sequential aspects of monitoring, the results showed that the monitoring of motivation predicts the monitoring of task definition, leading to task enactment. The results suggest that motivation is embedded in regulation phases. The current study sheds light on idiographic methods that have implications for individual learning analytics.

Notes for Practice

- Monitoring motivation fuels student learning during early phases of studying.
- Acknowledging monitoring has positive effects on other monitoring events.
- Modelling within-person variance and temporal network analysis offer a possible solution to the limitations of group-level methods.

Keywords

Self-regulated learning, collaborative learning, network analysis, psychological networks, idiographic network analysis

Submitted: 16/01/21 — **Accepted:** 20/10/21 — **Published:** 11/03/22

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1. Introduction

During the last decade, there has been a growing body of research indicating that students who engage in self-regulated learning (SRL) have strong academic learning outcomes (Lai et al., 2018), can find alternative strategies to overcome challenges during learning (Malmberg et al., 2015), and are able to stay motivated in order to reach their learning goals (Mega et al., 2014). In summary, SRL can provide powerful explanations for how individuals learn, and it has had a major impact on recent research related to learning and instruction. Recently, research focus has shifted from investigating how individuals learn individually to how learning happens in groups by taking into account the social learning context and the learning situation (Järvenoja et al., 2018). By taking this into account, the current study focuses on individual student monitoring associated with phases of SRL in the context of collaborative learning.

ISSN 1929-7750 (online).

Group learning is not merely a reflection of the SRL of the individual learners, but it is a complex combination of all the learners' contributions to the groups' collective effort, reciprocal interactions, and joint attention (Barron, 2003). Learners in collaborative groups share information, search for joint solutions to the task, and sustain a shared understanding of the task (Iiskala et al., 2011). In order to engage in collaborative learning and achieve joint learning goals, learners need to continuously monitor their learning and that of their group members (Hadwin et al., 2017). By engaging in metacognitive monitoring, learners compare their learning products generated at any point during the learning process (cognitive level) with the standards or goals set for learning (metacognitive level) (Winne & Hadwin, 1998). Standards are generated by the learner based on internal conditions of the task, such as learner beliefs, motivational state, and task knowledge, and external conditions of the task (Winne 2014). Standards include information about learners' understanding of the subject matter and the proper procedures to accomplish the task in line with the learning goals (Hacker, 1998; Perry & Winne, 2006). In other words, when engaging in metacognitive monitoring, learners actively think about their learning and the factors that affect it.

Metacognitive monitoring is always an internal mental process, but in collaborative situations, it can be externalized via visible interactions with other group members. When metacognitive monitoring is externalized, it can help to maintain shared mental models and to support effective group work (Fransen et al., 2011). Moreover, when monitoring is externalized, it can prompt other group members to evaluate their progress toward the learning goal and influence the group members' motivation levels, task understanding, goals and plans, task executions, and evaluation through an agreement between them (Iiskala et al., 2011). Previous research on monitoring has focused on specific aspects of monitoring, such as the valence of monitoring (Sobocinski et al., 2020), and different types of monitoring, for example, the monitoring of goals (Harkin et al., 2016) or the monitoring of motivation (Wolters, 2003). In recent literature, monitoring has been studied in terms of the context it emerges in, focusing on how it interacts with other learning processes (Ben-Eliyahu & Bernacki, 2015). On one hand, when researchers examined the relationship between monitoring and regulation, they found that metacognitive monitoring, when used by learners, stimulates joint knowledge construction (Malmberg et al., 2017). On the other hand, if externalized monitoring between group members is ignored, it leaves less space for interaction that benefits collaboration and regulation (Strauß & Rummel, 2021). However, according to models of SRL, metacognitive monitoring allows learners to change the ways they regulate their learning to be consistent with their learning goals (Hadwin et al., 2017). This study seeks to answer questions related to how the monitoring events of individual students associated with phases of SRL coexist temporally and progress sequentially during collaborative learning. This is important since the ways in which individual students perform metacognitive monitoring provide fuel for SRL on an individual and a collective level. Thus, this study provides an alternative view of investigating how the metacognitive monitoring of individual students associated with phases of SRL occurs in the context of collaborative learning. Ultimately, regulation in the context of collaborative learning is constructed during learning and is affected by individual students' contributions.

1.1. Cyclical Phases of Regulated Learning

Regulated learning is composed of various phases, namely, task definition; planning; goal setting; engaging in task enactment; and, finally, reflection and evaluation guided by motivation, which follow each other in a recursive cyclical order (Winne & Hadwin, 1998; Zimmerman, 2000). Theoretical models of SRL (Winne & Hadwin, 1998; Zimmerman, 2000), however, emphasize that the phases of regulated learning do not necessarily occur during the learning process or in the proposed order, but, rather, they occur when there is a need to change or update conditions that determine each individual student's current state of learning. Accordingly, each phase has its own relevance in learning and understanding, since the phases determine the metalevel aspects of the task, such as how the task is understood, the types of plans generated and goals set, strategies used during task execution, and the evaluations made after and throughout the learning process.

Task definition refers to students' understanding of the task, including explicit task features, such as task criteria and components. Task definitions are guided by students' previous knowledge of the same types of tasks, and they set a foundation for how students approach the task (Winne & Hadwin, 1998). Earlier research has indicated that students often misinterpret the task and are unsure of its purpose (Hadwin et al., 2009). In addition, faulty task perceptions have been linked to poor task performance (Butler & Cartier, 2004; Greene et al., 2012). How students interpret the task (i.e., as easy or difficult) also determines the types of plans and goals they choose to use. For example, if learners perceive the task to be difficult, their goal might be to "pass the task" (Winne, 2010). Yet, the goals determine the types of plans students choose to use, such as investing more effort in studying and strategically planning how to study. During task execution, students approach the task in line with their goals and use different types of strategies to meet the goals. However, if there is a mismatch between the strategies used and the goals set for learning, students can update or change their initial understanding of the task, goals, or plans or strategies they are using. Finally, evaluation refers to students' reflections on the past—what went wrong and what did not. Based on the evaluation, learners can adapt their understanding of the task, goals and plans, or tactics and strategies (Winne & Hadwin, 1998). Each of the theoretical models of SRL acknowledges that these phases occur in a cyclical manner during the learning process; however, it is unclear how the phases of SRL are cyclical in a learning context.

ISSN 1929-7750 (online).

Models of SRL also recognize the role of motivation in the learning process (Pintrich 2004; Zimmerman, 2000). In general, motivation initiates and maintains learning as well as thoughts and feelings and can explain why learners employ particular methods of learning (Pintrich, 2000). Accordingly, motivational factors may explain why (or why not) students activate monitoring in certain phases of learning or why and how they engage in regulatory activities. Similar to monitoring, motivation can also function as a part of different phases of the SRL cycle, in which it dynamically emerges and fades depending on situational needs (Järvenoja et al., 2015). Motivation can also be monitored and regulated when needed. Despite the acknowledgement of motivation as an essential part of the cyclical phases of regulated learning (Cleary & Zimmerman, 2012), there have only been a few studies on how motivation is actually monitored in relation to how the cyclical process of SRL is monitored (Järvelä et al., 2018; Zheng & Yu, 2016).

Acknowledging regulation, including motivation regulation, as a cyclical and contextual process has also influenced contemporary research highlighting the importance of examining the sequential and temporal characteristics of regulation in individual and collaborative leaning contexts (Molenaar & Järvelä, 2014). However, most of the research focusing on regulation in the context of collaborative learning has investigated regulation on a group level and passed over the individual student contribution to the regulation of groups that is realized through metacognitive monitoring, evidenced by interactions. However, the idea that regulation at the individual level takes place in social interaction, whereby self-regulating individuals influence each other by integrating self-regulatory processes interdependently and concurrently, has not yet emerged within the framework of social regulation. In other words, both personal and social forms of regulation are needed to understand regulation in the context of collaborative learning (Volet et al., 2009). Furthermore, when learning regulation is considered as a temporal and sequential process, it is crucial to consider how regulation actually occurs as individual actions "in situ" (Järvelä et al., 2021). Fortunately, recent advances in network science provide a methodological approach that allows us to investigate monitoring in individual group members in relation to the regulated learning phases present in collaborative learning. This paper applies psychological networks and temporal network analysis techniques to explore how within-person monitoring events associated with phases of SRL coexist temporally and sequentially during collaborative learning. In particular, the study seeks to answer how the monitoring events of individual students associated with phases of SRL coexist contemporaneously (i.e., concurrently) and sequentially (i.e., follow each other) during collaborative learning.

2. Methods for Studying SRL as a Cyclical Event in Collaborative Learning

Due to the complexity of SRL, there has been increasing interest in explaining how phases of regulation interact with and influence each other and how they connect with each other temporally and sequentially (Malmberg et al., 2017; Molenaar & Chiu, 2014). The sequential characteristics of regulated learning consider how regulation processes typically follow each other, while temporal characteristics reveal when regulation processes typically occur during the learning session or over time (Reimann et al., 2014). The strength of sequential and temporal analysis is in its ability to inform the order and time of regulation processes, including the most prominent transitions between regulation processes. Methodologically, the focus of SRL research has moved toward investigating events that unfold in real time during learning (Molenaar & Chiu, 2014). This is mostly because events that build regulation during learning interact with each other over time and therefore influence how regulation is shaped within and across learning situations. Typically, in the field of SRL, such sequential and temporal analysis has focused on either the SRL of individual students or group SRL, which aggregates the data of multiple people for the same event (Malmberg et al., 2017; Sobocinski et al., 2017).

Malmberg and colleagues (2017) examined the temporal sequences of regulated learning processes of groups that collaborated over two months. The temporal analysis showed that collaborative interactions focused on task execution led to socially shared planning, and that metacognitive monitoring facilitated task execution. Malmberg and colleagues (2015) compared the progress of socially shared regulation between low- and high-performing groups. The students in the high-performing group experienced a variety of challenges and employed SRL strategies throughout the task, suggesting that in these groups, although students faced challenging learning situations, they could overcome the challenges and improve their final learning outcomes because they were able to regulate their learning. Sobocinski and colleagues (2017) compared the temporal order of regulatory phases and types of interaction in groups participating in high- and low-challenge sessions. Their results showed that in high-challenge sessions, groups switched between the forethought and performance phase, which is considered a sign of metacognitive monitoring, more often than in low-challenge sessions. Bakhtiar and colleagues (2018) conducted a cross-case analysis of two groups collaborating on an online text-based assignment. The findings underline the importance of emotional regulation during planning to achieve a positive socioemotional climate and identify negative emotions that impede shared regulation in the face of challenges.

Despite the above-mentioned studies having provided understanding about temporal progress of regulation in the context of collaborative learning by aggregating the SRL interactions of multiple people, they have been limited in terms of describing how individual students contribute to joint regulation. Psychological networks offer a within-person view of the interplay between different constructs and the temporal evolution thereof that could be used as grounds for personalized support. The next section covers these concepts in detail with examples.

2.1. Network Analysis

In the next section, we review the network analysis and, in particular, psychological networks. First, we show the conceptual grounding of psychological and temporal networks. Second, we show how these networks are used to study within-person phenomena and show with SRL examples the differences between within-person and group-level analysis. Third, we conclude this section by comparing psychological networks to other methods and discuss how psychological networks are particularly useful in analyzing a complex temporal process such as SRL.

2.2. The Cognitive Process as a Networked System

Representing elements of the cognitive and social processes as a network is an established research method. Such representation has given researchers a way to visualize the structure of these processes, to measure the magnitude of association between their elements, and to devise statistical indices that allow them to precisely interpret the resultant graphs (Dado & Bodemer, 2017; Saqr et al., 2020). In education, research on networks spans three decades. In the field of social network analysis (SNA), researchers have, for example, used networks to visualize the patterns of interactions in collaborative groups, study the roles students play in the collaboration, rank students' activities, or predict performance (Dado & Bodemer, 2017; Saqr et al., 2019). While such powerful methods have contributed enormously to our understanding of the learning process, they are lacking in terms of robust probabilistic statistical methods and within-person and longitudinal analysis. Therefore, psychological networks have been conceptualized.

2.3. Psychological Networks

Recent advances in network sciences have led to the remarkable growth of probabilistic psychological network models, often as graphical Gaussian models (GGM) (Epskamp et al., 2018b). Psychological networks map the relationships between the elements of the cognitive or sociological phenomena (e.g., SRL) as a complex system by estimating a network where the nodes are variables (e.g., SRL phases) and the edges are the partial correlation coefficients between these variables (Artner et al., 2020; Borsboom, 2017; Epskamp et al., 2018b; Hamilton et al., 2019; Hevey, 2018). Similar to multiple regression, partial correlations estimate the correlations after controlling for all other variables in the network, eliminating the possible effect of confounding variables (Artner et al., 2020). This is particularly useful when there are multiple dependencies; for example, task enactment depends on motivation, and motivation may depend on goal setting or feedback. Thus, in partial correlation networks, two nodes are connected if, and only if, there is a covariance between these nodes that cannot be explained by any other variable in the network (Epskamp et al., 2018b; Hevey, 2018). Thus, the resultant networks only show the significant relationships and eliminate the spurious negligible relationships. Psychological networks are undirected, signed (show positive or negative association between variables), and weighted (show strength of associations). Therefore, the psychological network models offer "hypothesis generating structures, which may reflect potential causal effects to be further examined" (Hevey, 2018). As such, psychological networks offer great potential for studying a complex temporal process such as SRL and overcoming the shortcomings of existing methods in terms of rigorous inferential statistics, elimination of spurious relationships, and accounting for positive and negative covariation. The fictional example in Figure 1 illustrates the complex interplay between four constructs: motivation, engagement, stress, and work on assignment. Motivation is positively associated with engagement (shown as a thin blue line), motivation is also strongly associated with work on assignment (shown as a thick blue line), and stress is negatively associated with work on assignment. The example shows how a psychological network accounts for the complex interplay between the four variables, the direction of association, and the strength thereof.

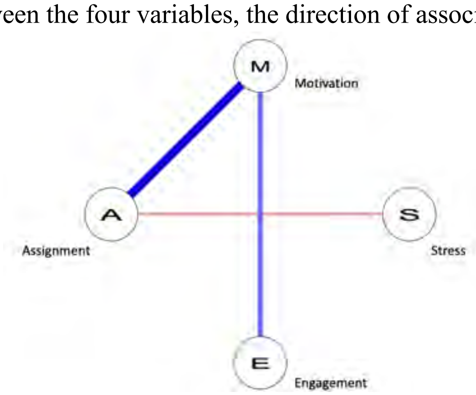

Figure 1: A psychological network showing the complex interplay between motivation, engagement, stress, and work on assignment: the circles are variables, blue lines are positive partial correlations, red lines are negative partial correlations, and the thickness of the line is proportional to the magnitude of the correlation.

2.4. Graphical Vector Autoregression (Temporal Networks)

An extension of psychological network methods has enabled us to model temporal processes, that is, how a variable predicts another in the next time window using graphical vector autoregression (VAR). VAR estimates a directed network (in contrast to undirected in partial correlation networks); the nodes are variables (e.g., motivation, behaviour, or attitude), and the links between them are temporal relationships (a variable predicts another in the next time window) (Epskamp et al., 2018b; Saqr & Lopez-Pernas, 2021a, 2021b). This is commonly represented by drawing an arrow from the node that represents the variable (e.g., motivation) to the variable that it predicts in the next time window of measurement (e.g., engagement). To explain this, we present an example in Figure 2. We created a simulated dataset about working and achievement within an individual from data collected daily for a month. The graph shows that motivation predicts work (shown as a blue arrow), as well as feelings of achievement of goals within the next day. Similarly, working predicts feelings of goal achievement. However, engaging with work predicts slight stress the next day (shown as a red arrow), and having stress negatively predicts feelings of achievement.

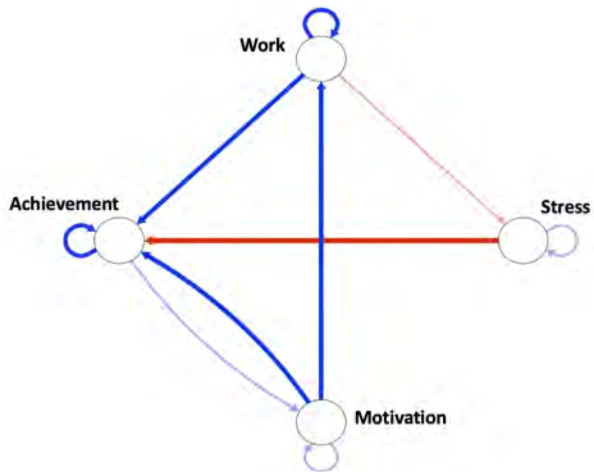

Figure 2: A fictional temporal network of four constructs. The circles are variables. Blue lines are positive partial correlations. The thickness of the line is proportional to the magnitude of the correlation. The direction of the arrow points to the direction of the temporal correlation.

2.5. Between- and within-Person

Group-based statistics commonly referred to as nomothetic methods use data from a group of individuals (e.g., a school) to derive group-level statistics (e.g., mean or correlation) that describe the "state of affairs" or normative laws and therefore to derive recommendations based on the analysis. For instance, a researcher would test the correlation between students' self-regulation and their grades by collecting self-regulation data from a school and calculating the correlation with grade. However, group-level averages poorly describe any individual within the group (Molenaar & Campbell, 2009; Fisher et al., 2018; Winne et al., 2017). In fact, it has long been noted that the notion that group-level statistics applies to all individuals in a sample is poorly supported by empirical evidence (Molenaar & Campbell, 2009). Therefore, an approach that brings the individual (the origin of the process) into focus is needed. Idiographic methods (i.e., within-person methods) rely on within-person analyses to understand and optimize the individual process (Epskamp et al., 2018b; Lamiell, 1981; Molenaar & Campbell, 2009). The abundance of intensive time-stamped data (time series) has led to the existence of enough observations of individual subjects (e.g., experience sampling methods, observational data, and physiological data) to enable the study of an individual as a unique case ($N = 1$) (Epskamp et al., 2018b; Molenaar, 2004; Saqr & Lopez-Pernas, 2021a, 2021b). Such time-series data are amenable to multivariate time-series analysis or the graphical VAR (Epskamp et al., 2018b). Furthermore, idiographic methods offer a possible solution to the limitations of group-level methods for the study of a dynamic process that unfolds over time within the individual (e.g., self-regulation). We take advantage of such time-stamped data in this study and apply idiographic within-person analysis to understand the SRL process and the temporal dynamics thereof. An illustrative example is presented in Figure 3, in which a fictional study evaluates the correlation between students' self-reflection on their learning, coded as "reflect," and their grades. In Figure 3A, the group-based analysis computes the correlation between students' grades and "reflect" scores of a group of students at a single time point, that is, a cross-sectional sample, which was time point T5 in our example. Figure 3B shows the within-person analysis, by collecting multiple data points for the same student and using such data to compute the correlation between the student's own "reflect" scores and their grades over multiple time points. As the example shows, while the group-level correlation between grades and "reflect" was statistically significant and positive ($r = 0.7$, $p = 0.03$), it was statically significant and negative ($r = -0.7$, $p = 0.04$) for the student in Figure 3B. Also, it is worth noting that group-level data are cross-sectional, while within-person data are temporal, allowing for temporal modelling.

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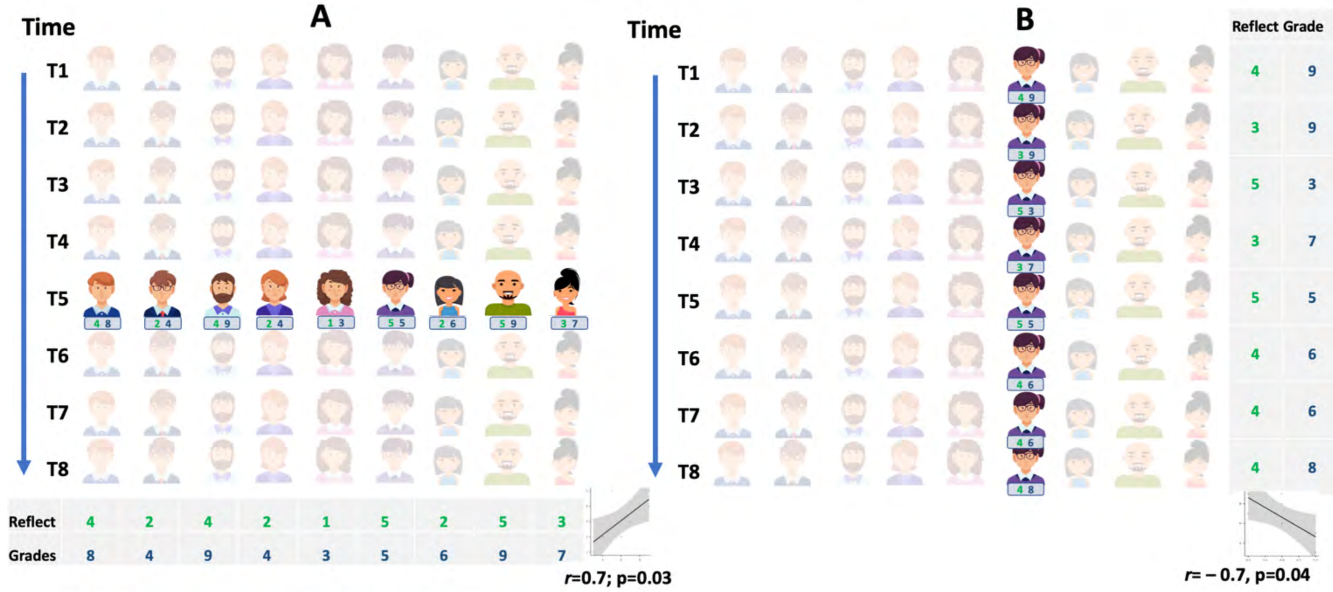

Figure 3A: Group-based analysis computes the correlation between students' grades and "reflect" scores at time point T5.

Figure 3B: The correlation between a single student's "reflect" scores and their grades over multiple time points. Correlation is positive (r = 0.7, p = 0.03) on the group-level statistics; however, it is negative for the student (r = −0.7, p = 0.04) in Figure 3B.

2.6. How Psychological Networks Differ from Other Methods

Process and sequence mining has been used extensively to study students' strategies, map their approaches to learning, and classify them according to their tactics (Bogarín et al., 2018; Peeters et al., 2020; Saint et al., 2020). Similarly, epistemic network analysis, lag sequential analysis, and social network analysis offer a rich toolset for studying the relationship between coded constructs and several mathematical indices (e.g., centrality measures). While such powerful methods have contributed enormously to our understanding of the learning process, they are lacking in terms of robust probabilistic statistics (Saqr et al., 2021). The representation and estimation of psychological networks (e.g., GGM) and VAR temporal networks allow the *idiographic* assessment of the complex interactions of the within-person dispositions and their temporal dynamics, a capability that is offered by psychological networks and lacking in other methods reviewed earlier. Furthermore, idiographic methods offer a possible solution to the limitations of group-level methods for the study of a dynamic process that unfolds over time within the individual (e.g., self-regulation). Such capabilities offer the in-depth exploration of the individual phenomena and the progression of behaviour, predict future behaviour, and create relevant intervention. Research in education has started to harness the power of psychological networks. Examples include Li and colleagues (2020), who used psychological networks to study the complex interplay between different self-regulatory learning behaviours, and Saqr and colleagues (2021), who studied SRL in academic writing settings. Similarly, VAR temporal networks were used to study the within-person temporal unfolding of SRL behaviours (Saqr & Lopez-Pernas, 2021a, 2021b). The present study addresses the power of idiographic methods (within-person network analytics) to investigate the monitoring events of individual students in the context of collaborative learning. Three research questions were developed:

1. How do the different monitoring events of individual group members coexist temporally during collaborative learning?
2. What is the temporal sequence of the different monitoring events of individual group members during collaborative learning?
3. How do the different monitoring events influence each other during the temporal process of collaborative learning?

3. Methods

The participants (*N* = 12, age 16–17 years, three female and nine male) were high school students enrolled in an advanced physics course. The course was an elective, and it required students to have completed two other physics courses. All participants were informed of the details of data collection and told that participation would not affect their grade in any way and that they could revoke their consent at any time during data collection. All 12 students gave written consent to participate in the study.

The course consisted of 18 lessons, designed by both the researchers and the teacher, with a duration of 75 minutes each. Each of the 18 lessons involved a short introduction to the topic by the teacher followed by collaborative group work related to the topic. The students collaborated in the same groups throughout the course. The collaborating groups were formulated based on the heterogeneity of learning regulation profiles for the sake of between-team comparability. The students were asked to fill out the cognitive and metacognitive strategies section of the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al., 1993) to determine their self-regulation profile. The students were classified into three groups of self-regulation (low, middle, and high) based on their score from the questionnaire. Each group included one student from each category.

The final six lessons took place at the LeaF Research Infrastructure (https://www.oulu.fi/leaf-eng/), which is located within short walking distance of the school. The centre was designed to observe collaborative work and unobtrusively collect video data. These lessons followed the regular schedule of the course, and the students arrived at the centre with their teacher. The last six lessons were selected, since the previous lessons included mainly teacher demonstrations and were less focused on hands-on collaborative work. The tasks during these last six lessons included designing experiments for measuring the speed of light and the thickness of hair and conducting hands-on experiments using lasers, mirrors, lenses, prisms, and a double split to study reflection, refraction, dispersion, and interference. In addition, the tasks were challenging and required genuine collaboration. A total of 18 h 53 min of video data was collected during the 18 sessions.

3.1. Video Data Analysis

The analysis began by first locating the monitoring utterances of the students from video data. Monitoring was identified to take place when an individual group member made a verbal remark on the group's collaborative learning process. The monitoring utterances were then categorized using qualitative content analysis, according to the SRL phase in which they occurred. In addition to the SRL phase categories, a category was created for monitoring utterances that were related to motivation. This resulted in five qualitatively different categories for monitoring: (1) task definition, (2) goal setting and planning, (3) task enactment, (4) evaluation, and (5) motivation (Table 1).

After the monitoring utterances were located and categorized, each student's subsequent acknowledgement of the monitoring was defined. Acknowledgement of monitoring could be identified through a variety of reactions that encompassed verbal responses as well as actions and gestures responding to the monitoring. If any type of acknowledgement was observed, it was coded as a "YES," indicating a complying/confirming response to monitoring. The reaction code (YES) was implemented only when it was possible to directly interpret that the reaction corresponded to the preceding monitoring utterance (Table 1).

After the final coding was completed, the reliability of the coding for monitoring was ensured by selecting 20% of the utterances to be classified by an independent coder. This resulted in 84.95% agreement, Cohen's $\kappa = 0.74$, indicating good agreement (Fleiss, 1981). Finally, the discrepancies were discussed until consensus was reached.

Table 1. Coding Scheme of Monitoring Categories and Data Examples

Phase Category	Description	Examples
Phase 1: Task definition	In this phase, the students form an understanding of the task and its affordances and constraints. They may also redefine their understanding of the task as they work through it. Learners can also search for additional information or ask for help if the task instruction is unclear.	"So did we have to do this, too?" "What is this concept?"
Phase 2: Setting goals and plans	After the students have formed an understanding of the task, it is time to set goals and make plans on how to reach them. What standards are used to identify whether the goal has been met? Will group members use trial and error as an approach to problem solving, or will they first gather knowledge?	"Should we do it the same way it was originally done?" "Our aim is to pass this course." "How many lectures do we have before the exam?"
Phase 3: Task enactment	In this phase, the students actively work on the task and monitor their progress using the standards. The students may also monitor other cognitive attributes, such as how much effort they are putting into the task.	"How should we proceed with this?" "Should we check if this is correct?"
Phase 4: Evaluation	This phase is usually at the end of the task. Strategies and methods of working are evaluated and adjusted for future purposes. The goal is to make the work easier in the future.	"We didn't manage to do all of these." "Didn't we do the same type of experiment last week?" "Today our group worked well!"
Phase 5: Motivation	Expressing annoyance or interest	"I am so poor in drawing; who would like to draw?" "This microphone is so annoying!"
YES: Reacting or agreeing for monitoring	Acknowledging previous monitoring utterance, verbal responses as well as actions and gestures	"Yes, we could explain more here." "So then it means that…" [Nodding approvingly]

In total, 1,391 monitoring events were coded. Monitoring during the task enactments occurred the most ($f = 1{,}008$), whereas evaluation occurred the least ($f = 36$). In total, "YES" indicating agreement for a previous monitoring utterance occurred 1,138 times. "YES" occurred the most after the task enactment ($f = 837$), whereas "YES" occurred the least ($f = 26$) after evaluation. Table 2 presents the frequencies of the occurrences of the monitoring and related YES reactions in different SRL phases.

Table 2. Frequencies of Monitoring and "YES"

Regulation Phase	*f*	YES *f*
Planning and goal setting	57	39
Task understanding	227	203
Task enactment	1,008	837
Evaluation	36	26
Motivation	63	33
	1,391	1,138

3.2. Network Analysis

A time series of all the interactions was constructed by aggregating the frequency and duration of each action within a window of 30 seconds (Kossinets & Watts, 2006; Shaffer et al., 2016; Shaffer et al., 2009). The time series was detrended using the method described by Epskamp and colleagues (2018b). Time series are frequently used methods in several disciplines (e.g., physics, econometrics, and meteorology) to analyze individual data ($N = 1$); they allow researchers to understand the trend, the fluctuations, and the temporal dependencies in the data (Jebb et al., 2015). Since the goal was to analyze the temporal and relational aspects of different SRL phases, the VAR model was used. VAR models are an extension of the commonly used univariate autoregression models to enable multiple variables to be analyzed. Recently, VAR models have been used in the study of psychological phenomena, shedding light on the temporal progression, individual aspects, and dynamics of psychological processes within individual people (Epskamp et al., 2018a, 2018b; Fisher et al., 2017).

To understand the sequential temporal dependencies, we constructed a temporal network by estimating a graphical VAR model on the entire within-subjects centred data set, using the GraphicalVAR package and the sample means of every subject on every variable as a plug-in for the within-subject means (Epskamp et al., 2018a). The GraphicalVAR package estimates the temporal and contemporaneous networks, plots the resulting networks, and calculates the centrality measures (see Epskamp and colleagues (2018a) for a full review and detailed methods). The temporal network captures future events as a sequence of current events (lagged effects). For example, if an individual is motivated now, they are going to work on the task next. To account for multiple comparisons, the model was regularized using a graphical least absolute shrinkage and selection operator (GLASSO). The GLASSO algorithm has been shown to retrieve the true structure of networks when it is used to estimate the partial correlation networks (Epskamp et al., 2018a). The regularization removes spurious and negligible edges, resulting in a sparse and interpretable network. Only significant edges were included in the analyzed network.

To understand how monitoring events coexist temporally, a fixed-effects contemporaneous network (within-person) was calculated using the residuals of the temporal network, which captures events faster than that used within the time window (i.e., within less than 30 seconds) or, roughly speaking, what is happening co-temporally in the same time window (e.g., when an individual performs a task while simultaneously getting motivated). A 30-second time frame was selected because events in a data set were coded per second, and a 30-second time window fully captured all the coded events, with the exception of one event, which was captured with 99% confidence. The networks were constructed using partial correlation with LASSO regularization.

Two centrality measures were calculated:

1. Strength centrality is the sum of the connection strengths of a node connection (partial correlation coefficients). Regardless of the sign (the absolute values), a node is expected to have higher degree if it is strongly correlated (positively or negatively) to other nodes. In other words, the node drives the connectivity of the networks.
2. Expected influence refers to the sum of the strengths of all the connections of a node (partial correlation coefficients), taking into account the sign (positive or negative) and thus reflecting how much a node can drive the connectivity on the positive side. A node is expected to have higher expected influence if it is positively and strongly correlated with other nodes.

For a detailed description of the methods, algorithms, and calculation methods of the GraphicalVAR package, see Epskamp and colleagues (2018b).

4. Results and Discussion

4.1. How Do the Different Monitoring Events of Individual Group Members Coexist Temporally during Collaborative Learning?

The targets of monitoring included task definition (TD), goal setting and planning (GP), task enactment (TE), evaluation (EV), motivation (ME), and students expressing agreement (YES). Figure 4 presents an average of the contemporaneous network of relationships from the 12 students. The contemporaneous network shows the events that exhibit co-temporal dependence within a shorter timeframe than the time window of measurement (30 seconds). A blue line from one node to another predicts the monitoring target. A red line indicates that the monitoring events are less likely to follow. The thickness of a line indicates the strength of the connection.

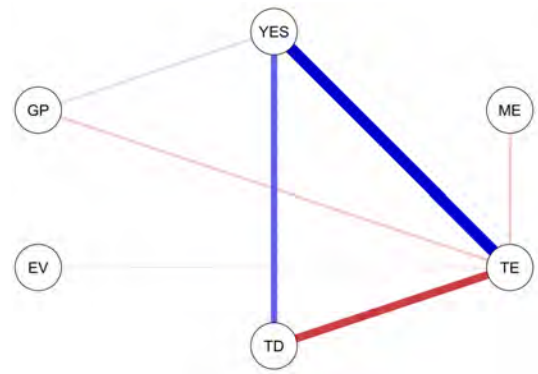

Figure 4. Contemporaneous (within-person) network showing events that were co-temporally connected in a timeframe of less than 30 seconds.

The results show that monitoring task enactment (TE) is very strongly associated with agreement (YES). Similarly, agreement (YES) is associated with monitoring task definition (TD). Monitoring task definition is negatively associated with monitoring task enactment, which means that they do not co-exist within the same time window. Similarly, monitoring goals and planning and monitoring task enactment are negatively correlated, but monitoring goal setting and planning (GP) and agreement (YES) are weakly positively correlated. Evaluation (EV) exists but is not associated with any other phases of SRL in terms of monitoring. Table 3 provides further information about the magnitudes of partial correlations. In summary, monitoring phases such as task definition, goal setting and planning, and task enactment do not coexist co-temporally, but each of them has a correlation for agreement. In other words, they occur in different phases following each other rather than existing together.

Table 3. Partial Correlations of Co-temporal Dependence of Monitoring Events

Variable	YES	ME	TE	TD	EV	GP
YES	–					
ME	0.01*	–				
TE	0.35*	−0.06*	–			
TD	0.18*	–	−0.23*	–		
EV	–	–	−0.03*	–	–	
GP	0.04*	–	−0.06*	–	–	–

YES = agreement, ME = motivation, TE = task execution, TD = task definition, EV = evaluating, GP = goal setting and planning. *Only significant partial correlations at the level of $p < 0.05$ are reported.

4.2. What Is the Temporal Sequence of the Different Monitoring Events of Individual Group Members during Collaborative Learning?

The targets of monitoring included task definition (TD), goal setting and planning (GP), task enactment (TE), evaluation (EV), motivation (ME), and the students expressing agreement (YES). Figure 5 represents a temporal network showing events that sequentially and temporally depend on each other (the occurrence of a phase predicts the occurrence of another in the next time window, which is 30 seconds). Figure 5 presents the average within-person temporal network of transitions from the 12 students. A blue arrow from one node to another predicts the monitoring target. A red arrow indicates that the monitoring events are less likely to follow each other. The thickness of an arrow indicates the strength of the connection.

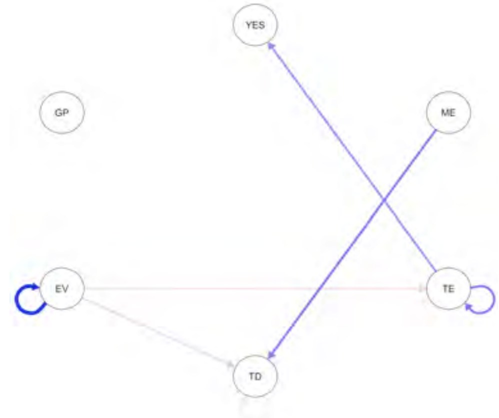

Figure 5. Temporal network (within-person) showing events that are sequentially connected.

In the temporal network graph in Figure 5, monitoring motivation (ME) predicts monitoring task definition (TD). Task definition predicts itself, as indicated by the loop. Evaluation (EV) predicts itself and the occurrence of task definition, and task definition predicts task enactment (TE). Task enactment is the strongest predictor of task enactment (shown as a loop) as well as the only predictor of agreement within a person. Goals and planning (GP) is temporally independent of all other phases and is loosely predictive of itself. Table 4 provides further information on the magnitudes, indicating that each of the reported values is significant with value greater or smaller than 0.00.

Table 4. VAR Values of Sequentially and Temporally Dependent Monitoring Events

Variable	YES	ME	TE	TD	AD	GP
YES	–	–	–	–	–	–
ME	–	–		0.09*	–	–
TE	0.08*	–	0.09*	–	–	–
TD	–	–	0.01*	0.02*	–	–
AD	–	–	−0.03*	0.04*	0.16*	–
GP	–	–	–	–	–	0.01*

YES = agreement, ME = motivation, TE = task execution, TD = task definition, EV = evaluating, GP = goal setting and planning. *Only significant partial correlations at the level of $p < 0.05$ are reported.

4.3. How Do the Different Monitoring Events Influence Each Other during Collaborative Learning?

The centrality measures point to the monitoring events including agreement that drive the network connectivity the most, in other words, the monitoring events that would stimulate other actions. Figure 6 illustrates (left) the strength of each event for other events and (right) the expected influence for other events. The five monitoring events including agreement are represented on the *y*-axis. The magnitude of each event is represented on the *x*-axis.

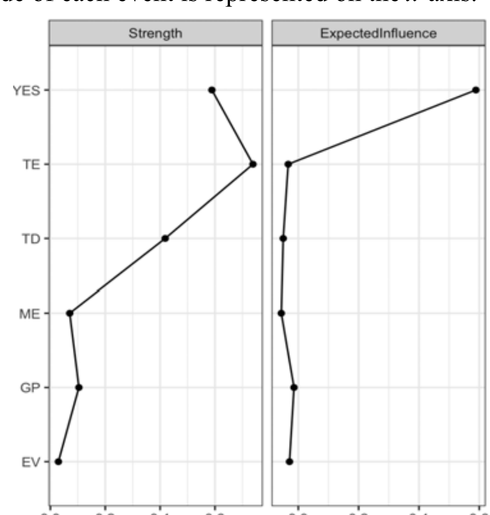

Figure 6. Strength and expected influence of monitoring events.

The centrality measures point to the nodes that drive the network connectivity the most, that is, that would stimulate other actions. The strength centrality shows that task enactment followed by reaction and task definition were the most central actions. This means that they are the ones that stimulated the other actions, such as motivation, goal setting and planning, and evaluation. However, the expected influence centrality shows that only agreement was the most important action; as the name implies, expected influence considers the direction of the correlation, so agreement is expected to stimulate all other actions positively.

5. Conclusion

This study investigated how monitoring events are associated with phases of regulation during collaborative learning. However, due the exploratory nature of the research, the findings should be interpreted with caution. With regard to the first research question, temporal coexistence of monitoring events, the results show that monitoring phases (i.e., task definition, goal setting and planning, and task enactment) do not correlate with each other co-temporally but are all linked with an agreement that indicates a continuum in monitoring attempts. This result indicates that in the context of collaborative learning, switching between phases of the regulation cycle does not occur in short-term sequences. Rather, monitoring within a certain phase leads to enactment by the monitoring group member as well as other group members before the group progresses to other phases of regulation in their temporal collaboration. Earlier research in the context of collaborative learning has found similar results. For example, Fransen and colleagues (2011) argue that in collaborative learning, monitoring occurs as a result of shared and externalized mental models of the task, and it increases awareness of the current stage in the learning process. The current study extends these results, finding that there is a continuation of the monitoring activity within the same phase of SRL in collaborative learning. Sobocinski and colleagues (2020) support this finding by demonstrating that externalized monitoring events afford changes in regulation. Furthermore, the results show that there is an immediate reaction for monitoring task execution, task definition, and goal setting and planning, but not for monitoring during evaluation or motivation. Earlier studies have indicated that evaluation rarely occurs during learning (e.g., Malmberg et al., 2017). Similarly, earlier results have indicated that externalized attempts to regulate motivation are relatively rare in collaborative learning (Järvenoja et al., 2020). Research also indicates that motivation monitoring does not always lead to further regulatory acts (Mänty et al., 2020), but monitoring as an acknowledgement of a motivational challenge can lead to restored on-task performance through phases of SRL. An awareness of situational challenges that are externalized through monitoring in collaborative learning increases possibilities for future regulation and collaborative learning in general (Järvenoja et al., 2020).

Regarding the second research question, which is concerned with the temporal sequence of monitoring events, the results show that motivation predicts the monitoring of task definition, leading to task enactment and agreement. In other words, the monitoring of motivation fuelled students' learning during the early phases of task execution when they were still unsure about the nature of the task. Bakhtiar and colleagues (2018) also found that positive or negative motivational and emotional interactions set a foundation for collaborative learning, and this type of interaction occurs especially in early phases of learning. The temporal analysis in this study shows that there was a recurrent loop from task definition to itself. The result highlights the importance of constructing joint and accurate task understanding in collaborative learning. This conclusion was also drawn in a study by Rogat and Linnenbrink-Garcia (2011). In addition, this might also explain why students did not monitor previous phases of SRL during task execution but rather continued monitoring task execution, which was shown as a loop between task execution and agreement. In this study, monitoring during task execution did not predict the switching of monitoring between other phases of SRL. This might indicate that during the task enactment, students monitor errors during their task enactment rather than adjust other SRL phases. This is evident in the loop between acknowledging and monitoring during the task execution. This result is similar to the finding by Sobocinski and colleagues (2017). They investigated regulation in collaborative learning and found that in high-challenge learning situations, students switched more often between goal setting and planning and task execution, whereas in low-challenge situations, students remained in task execution. This supports the findings from this study of similar sequential and temporal transitions between monitoring associated with SRL phases when aggregated between all the students.

With regard to the third research question, which explores how monitoring events influence each other, the results show that in the context of collaborative learning, the most influential event was acknowledging and continuing activity consistent with monitoring. The results demonstrate that acknowledging or agreeing to monitoring events prompted the other monitoring events. This result confirms that of earlier studies: when monitoring during collaborative learning is externalized, it can encourage other group members to evaluate their progress toward their learning goals and affect the motivation of the group, their task understanding, their goals and plans, their task executions, and their evaluation (Iiskala et al., 2011). However, merely externalizing monitoring is not enough; individuals also need to ensure and promote the progress of monitoring throughout the phases of SRL. There is a need for individuals to acknowledge monitoring, which is shown as a continuation of the activity.

This study used an idiographic, within-person contemporaneous and temporal network analysis approach, which has not yet been applied at this level of detail in the field of SRL. Such a network approach offers a robust estimation method, which considers the relationships between variables after controlling for all other variables in the network. This means that every visible link in the network both is significant, independent of collinearity with other variables, and represents a substantial dependence or association between the nodes (in our case, monitoring events) (Epskamp et al., 2018a, 2018b). In doing so, it offers an extension to the existing methods (e.g., process mining, which models the transitions between events, or epistemic network analysis, which models the co-temporal co-occurrence). Temporal network methods add a much needed statistical method to model sequential and temporal dynamics. By modelling within-person variance, temporal network analysis offers a possible solution to the limitations of group-level methods (which present a cross-sectional picture) by capturing the temporal profile and sequential patterns and, thus, providing a nuanced and rigorous method for studying a dynamic process that unfolds over time within the individual (e.g., self-regulation) (Fisher et al., 2018; Lamiell, 1981). Doing so allows us to answer the question of when certain events happen, identify their precedent factors, and investigate the relational dynamics between events (i.e., how the relationship between different events evolves over time) (Valsiner et al., 2009).

Idiographic methods (within-person) have been adopted within many fields to model temporal processes and to overcome the limitations of group-level analysis, since this method is difficult to apply at individual levels (Fisher et al., 2018), and recently in education (Li et al., 2020; López-Pernas & Saqr, 2021; Saqr et al., 2021; Saqr & Lopez-Pernas, 2021b). This study has explored the potential of such methods in a limited sample of learners. We aim to extend our work in the future by using larger samples and different learning scenarios and by examining the modelling of individual learners. An interesting future approach would be to investigate different monitoring and intervention techniques and identify network models that can give information on intervention or even monitor such intervention.

Temporal network methods that rely on within-person variance are not without limitations. The methods require intensive data collection within limited time periods, such as the use of video in our case or frequent surveys. Another limitation is the difficulty of defining the time window of measurement with little guidance or standards. However, as research increasingly relies on such methods, our understanding of norms and standards is improving. In this study, the results are aggregated across the tasks within an individual, but this does not necessarily mean that individuals monitor learning similarly across the tasks. In the future, the same method could be used to identify, for example, how individual monitoring differs between the phases of SRL or across the different domains or tasks and if the changes in the monitoring behaviours of individuals influence their learning performance. This could provide an understanding of the role of monitoring in learning. In addition, by using between-person analysis, it would be possible to investigate not only the monitoring of individual students throughout the phases but also that across groups. This would require a larger data set, including individuals and groups. This study had various limitations. The sample size was small, which precluded analysis at the group level. In terms of learning performance, each group was equal, which did not allow comparison between "successful" and "unsuccessful" monitoring. Also, we did not take the monitoring of group members throughout the phases of SRL into account. For example, the analysis on coexisting temporal monitoring did not show if other group members also acknowledged (or did not acknowledge) the monitoring event. Similarly, the analysis focusing on sequential and temporal aspects of monitoring did not reveal the typical contributions of other group members. Nevertheless, the current study elucidates idiographic methods that have implications for individual learning analytics, so that learners can gather their own data and interpret results to decide whether and how to adapt the regulation of learning.

In summary, this study examined individual student monitoring in relation to the cyclical phases of regulation in the context of collaborative learning by using temporal network analysis techniques. It contributes to the field of SRL in three ways. First, the study investigates individual monitoring actions in an authentic, everyday, collaborative learning context. By targeting the different phases of SRL and acknowledging the monitoring of motivation from utterances and expressions, the study captures, on a micro level, the monitoring of individual group members that is a basis for group-level regulation. Second, the study provides insight into contemporaneous and temporal network analysis to illustrate how the monitoring events associated with phases of SRL typically occur on an individual level in the context of collaborative learning. Third, the results of this study have the potential to contribute methodologically to the SRL literature by connecting the results of individual monitoring events to group-level, regulated learning phases. This type of approach could inform future studies on how and when individual monitoring events are aligned with the shared attempts of the collaborating groups to monitor their learning. This may eventually contribute to revealing how and why collaborating groups are successful in their learning and regulation.

Declaration of Conflicting Interest

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

Funding

This research is connected to the GenZ project (https://www.oulu.fi/university/genz-profiling-project), a strategic profiling project in human sciences at the University of Oulu. The project is supported by the Academy of Finland (project number 318930) and the University of Oulu.

Data collection was carried out with the support of LeaF Research Infrastructure (https://www.oulu.fi/leaf-eng/), University of Oulu, Finland.

References

Artner, R., Wellingerhof, P. P., Lafit, G., Loossens, T., Vanpaemel, W., & Tuerlinckx, F. (2020). The shape of partial correlation matrices. *Communications in Statistics—Theory and Methods*, *50*(23), 1–18. https://doi.org/10.1080/03610926.2020.1811338

Bakhtiar, A., Webster, E. A., & Hadwin, A. F. (2018). Regulation and socio-emotional interactions in a positive and a negative group climate. *Metacognition and Learning*, *13*(1), 57–90. https://doi.org/10.1007/s11409-017-9178-x

Barron, B. (2003). When smart groups fail. *The Journal of the Learning Sciences*, *12*(3), 307–359. https://doi.org/10.1207/S15327809JLS1203_1

Ben-Eliyahu, A., & Bernacki, M. L. (2015). Addressing complexities in self-regulated learning: A focus on contextual factors, contingencies, and dynamic relations. *Metacognition and Learning*, *10*(1), 1–13. https://doi.org/10.1007/s11409-015-9134-6

Bogarín, A., Cerezo, R., & Romero, C. (2018). A survey on educational process mining. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *8*(1), e1230. https://doi.org/10.1002/widm.1230

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry*, *16*(1), 5–13. https://doi.org/10.1002/wps.20375

Butler, D. L., & Cartier, S. C. (2004). Promoting effective task interpretation as an important work habit: A key to successful teaching and learning. *Teachers College Record*, *106*(9), 1729–1758. https://www.tcrecord.org/content.asp?contentid=11668

Cleary, T. J., & Zimmerman, B. J. (2012). A cyclical self-regulatory account of student engagement: Theoretical foundations and applications. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), *Handbook of Research on Student Engagement* (pp. 237–257). New York: Springer. https://doi.org/10.1007/978-1-4614-2018-7_11

Dado, M., & Bodemer, D. (2017). A review of methodological applications of social network analysis in computer-supported collaborative learning. *Educational Research Review*, *22*, 159–180. https://doi.org/10.1016/j.edurev.2017.08.005

Epskamp, S., van Borkulo, C. D., van der Veen, D. C., Servaas, M. N., Isvoranu, A. M., Riese, H., & Cramer, A. O. J. (2018a). Personalized network modeling in psychopathology: The importance of contemporaneous and temporal connections. *Clinical Psychological Science*, *6*(3), 416–427. https://doi.org/10.1177/2167702617744325

Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2018b). The Gaussian graphical model in cross-sectional and time-series data. *Multivariate Behavioral Research*, *53*(4), 453–480. https://doi.org/10.1080/00273171.2018.1454823

Fisher, A. J., Medaglia, J. D., & Jeronimus, B. F. (2018). Lack of group-to-individual generalizability is a threat to human subjects research. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(27), E6106–E6115. https://doi.org/10.1073/pnas.1711978115

Fisher, A. J., Reeves, J. W., Lawyer, G., Medaglia, J. D., & Rubel, J. A. (2017). Exploring the idiographic dynamics of mood and anxiety via network analysis. *Journal of Abnormal Psychology*, *126*(8), 1044–1056. https://doi.org/10.1037/abn0000311

Fleiss, J. L. (1981). *Statistical Methods for Rates and Proportions*. London, UK: Wiley. https://doi.org/10.1002/0471445428

Fransen, J., Kirschner, P. A., & Erkens, G. (2011). Mediating team effectiveness in the context of collaborative learning: The importance of team and task awareness. *Computers in Human Behavior*, *27*(3), 1103–1113. https://doi.org/10.1016/j.chb.2010.05.017

Greene, J. A., Hutchison, L. A., Costa, L. J., & Crompton, H. (2012). Investigating how college students' task definitions and plans relate to self-regulated learning processing and understanding of a complex science topic. *Contemporary Educational Psychology*, *37*(*4*), 307–320. https://doi.org/10.1016/j.cedpsych.2012.02.002

Hacker, D. J. (1998). Definitions and empirical foundations. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in Educational Theory and Practice* (pp. 1–23). Mahwah, NJ: Lawrence Erlbaum.

Hadwin, A. F., Järvelä, S., & Miller, M. (2017). Self-regulation, co-regulation and shared regulation in collaborative learning environments. In D. Schunk & J. Greene (Eds.), *Handbook of Self-Regulation of Learning and Performance* (second edition) (pp. 65–84). New York, NY: Routledge. https://doi.org/10.4324/9781315697048

Hadwin, A. F., Oshige, M., Miller, M., & Wild, P. M. (2009). Examining the agreement between student and instructor task perceptions in a complex engineering design task. In *Proceedings of CDEN/C2E2 Conference*. 27–29 July 2009, Hamilton, ON, Canada. https://doi.org/10.24908/pceea.v0i0.3692

Hamilton, M., Clarke-Midura, J., Shumway, J. F., & Lee, V. R. (2020). An emerging technology report on computational toys in early childhood. *Technology, Knowledge and Learning*, *25*, 213–224. https://doi.org/10.1007/s10758-019-09423-8

Harkin, B., Webb, T. L., Chang, B. P. I., Prestwich, A., Conner, M., Kellar, I., Benn, Y., & Sheeran, P. (2016). Does monitoring goal progress promote goal attainment? A meta-analysis of the experimental evidence. *Psychological Bulletin*, *142*(2), 198–229. https://doi.org/10.1037/bul0000025

Hevey, D. (2018). Network analysis: A brief overview and tutorial. *Health Psychology and Behavioral Medicine*, *6*(1), 301–328. https://doi.org/10.1080/21642850.2018.1521283

Iiskala, T., Vauras, M., Lehtinen, E., & Salonen, P. (2011). Socially shared metacognition within primary school pupil dyads' collaborative processes. *Learning and Instruction*, *21*(3), 379–393. https://doi.org/10.1016/j.learninstruc.2010.05.002

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

Järvelä, S., Malmberg, J., Haataja, E., Sobocinski, M., & Kirschner, P. A. (2021). What multimodal data can tell us about the students' regulation of their learning process? *Learning and Instruction*, *72*, 101203. https://doi.org/10.1016/j.learninstruc.2019.04.004

Järvenoja, H., Järvelä, S., & Malmberg, J. (2015). Understanding regulated learning in situative and contextual frameworks. *Educational Psychologist*, *50*(3), 204–219. https://doi.org/10.1080/00461520.2015.1075400

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

Järvenoja, H., Järvelä, S., Törmänen, T., Näykki, P., Malmberg, J., Kurki, K., Mykkänen, A., & Isohätälä, J. (2018). Capturing motivation and emotion regulation during a learning process. *Frontline Learning Research*, *6*(3), 85–104. https://doi.org/10.14786/flr.v6i3.369

Jebb, A. T., Tay, L., Wang, W., & Huang, Q. (2015). Time series analysis for psychological research: Examining and forecasting change. *Frontiers in Psychology*, *6*, 1–24. https://doi.org/10.3389/fpsyg.2015.00727

Kossinets, G., & Watts, D. J. (2006). Empirical analysis of an evolving social network. *Science*, *311*(5757), 88–90. https://doi.org/10.1126/science.1116869

Lai, C. L., Hwang, G. J., & Tu, Y. H. (2018). The effects of computer-supported self-regulation in science inquiry on learning outcomes, learning processes, and self-efficacy. *Educational Technology Research and Development*, *66*(4), 863–892. https://doi.org/10.1007/s11423-018-9585-y

Lamiell, J. T. (1981). Toward an idiothetic psychology of personality. *American Psychologist*, *36*(3), 276–289. https://doi.org/10.1037/0003-066X.36.3.276

López-Pernas, S., & Saqr, M. (2021). Idiographic learning analytics: A within-person ethical perspective. In *Companion Proceedings 11th International Conference on Learning Analytics & Knowledge* (LAK 2021), 12–16 April 2021, Online, Everywhere (pp. 369–374). ACM.

Li, S., Du, H., Xing, W., Zheng, J., Chen, G., & Xie, C. (2020). Examining temporal dynamics of self-regulated learning behaviors in STEM learning: A network approach. *Computers and Education*, *158*, 103987. https://doi.org/10.1016/j.compedu.2020.103987

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

Malmberg, J., Järvelä, S., Järvenoja, H., & Panadero, E. (2015). Promoting socially shared regulation of learning in CSCL: Progress of socially shared regulation among high- and low-performing groups. *Computers in Human Behavior*, *52*, 562–572. https://doi.org/10.1016/j.chb.2015.03.082

Mänty, K., Järvenoja, H., & Törmänen, T. (2020). Socio-emotional interaction in collaborative learning: Combining individual emotional experiences and group-level emotion regulation. *International Journal of Educational Research*, *102*, 101589. https://doi.org/10.1016/j.ijer.2020.101589

Mega, C., Ronconi, L., & De Beni, R. (2014). What makes a good student? How emotions, self-regulated learning, and motivation contribute to academic achievement. *Journal of Educational Psychology*, *106*(1), 121. https://doi.org/10.1037/a0033546

Molenaar, I., & Chiu, M. M. (2014). Dissecting sequences of regulation and cognition: Statistical discourse analysis of primary school children's collaborative learning. *Metacognition and Learning*, *9*, 137–160. https://doi.org/10.1007/s11409-013-9105-8

Molenaar, I., & Järvelä, S. (2014). Sequential and temporal characteristics of self and socially regulated learning. *Metacognition and Learning*, *9,* 75–85. https://doi.org/10.1007/s11409-014-9114-2

Molenaar, P. C. M. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement: Interdisciplinary Research and Perspectives*, *2*(4), 201–218. https://doi.org/10.1207/s15366359mea0204_1

Molenaar, P. C. M., & Campbell, C. G. (2009). The new person-specific paradigm in psychology. *Current Directions in Psychological Science*, *18*(2), 112–117. https://doi.org/10.1111/j.1467-8721.2009.01619.x

Peeters, W., Saqr, M., & Viberg, O. (2020). Applying learning analytics to map students' self-regulated learning tactics in an academic writing course. In H.-J. So, M. M. Rodrigo, J. Mason, & A. Mitrovic (Eds.), *Proceedings of the 28th International Conference on Computers in Education* (ICCE 2020), 23–27 November 2020, online (Volume 1, pp. 245–254). Asia-Pacific Society for Computers in Education. https://apsce.net/icce/icce2020/proceedings/paper_143.pdf

Perry, N. E., & Winne, P. H. (2006). Learning from learning kits: gStudy traces of students' self-regulated engagements with computerized content. *Education Psychology Review*, *18*, 211–228. https://doi.org/10.1007/s10648-006-9014-3

Pintrich, P. R. (2000). *The role of goal orientation in self-regulated learning.* In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 451–502). Academic Press. https://doi.org/10.1016/B978-012109890-2/50043-3

Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review*, *16*, 385–407. https://doi.org/10.1007/s10648-004-0006-x

Pintrich, P. R., Smith, D. A., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the Motivated Strategies for Learning Questionnaire (MSLQ). *Educational and Psychological Measurement*, *53*(3), 801–813. https://doi.org/10.1177/0013164493053003024

Reimann, P., Markauskaite, L., & Bannert, M. (2014). E-research and learning theory: What do sequence and process mining methods contribute? *British Journal of Educational Technology*, *45*(3), 528–540. https://doi.org/10.1111/bjet.12146

Rogat, T. K., & Linnenbrink-Garcia, L. (2011). Socially shared regulation in collaborative groups: An analysis of the interplay between quality of social regulation and group processes. *Cognition and Instruction*, *29*(4), 375–415. https://doi.org/10.1080/07370008.2011.607930

Saint, J., Gašević, D., Matcha, W., Uzir, N., & Pardo, A. (2020). Combining analytics methods to unlock sequential and temporal patterns of self-regulated learning. In *Proceedings of the 10th International Conference on Learning Analytics & Knowledge* (LAK 2020), 23–27 March 2020, Frankfurt, Germany (pp. 402–411). ACM. https://doi.org/10.1145/3375462.3375487

Saqr, M., & Lopez-Pernas, S. (2021a). Idiographic learning analytics: A definition and a case study. In *Proceedings of the 2021 International Conference on Advanced Learning Technologies (ICALT 2021)*, 12–15 July 2021, Tartu, Estonia (pp. 163–165). IEEE. https://doi.org/10.1109/icalt52272.2021.00056

Saqr, M., & Lopez-Pernas, S. (2021b). Idiographic learning analytics: A single student (N = 1) approach using psychological networks. In *Companion Proceedings of the 11th International Conference on Learning Analytics & Knowledge* (LAK 2021), 12–16 April 2021, Irvine, CA, USA (pp. 456–463). https://doi.org/10.13140/RG.2.2.10956.13443

Saqr, M., Nouri, J., & Fors, U. (2019). Time to focus on the temporal dimension of learning: A learning analytics study of the temporal patterns of students' interactions and self-regulation. *International Journal of Technology Enhanced Learning*, *11*(4), 398–412. https://doi.org/10.1504/ijtel.2019.10020597

Saqr, M., Viberg, O., & Peeters, W. (2021). Using psychological networks to reveal the interplay between foreign language students' self-regulated learning tactics. In *STELLA2020 CEUR Workshop Proceedings* (pp. 1–12). http://ceur-ws.org/Vol-2828/article_2.pdf

Shaffer, D. W., Collier, W., & Ruis, A. R. A. (2016). A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *Journal of Learning Analytics*, *3*(3), 9–45. https://doi.org/10.18608/jla.2016.33.3

Shaffer, D. W., Hatfield, D., Svarovsky, G. N., Nash, P., Nulty, A., Bagley, E., Frank, K., Rupp, A. R., & Mislevy, R. (2009). Epistemic network analysis: A prototype for 21st-century assessment of learning. *International Journal of Learning and Media*, *1*(2), 33–53. https://doi.org/10.1162/ijlm.2009.0013

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

Sobocinski, M., Malmberg, J., & Järvelä, S. (2017). Exploring temporal sequences of regulatory phases and associated interactions in low- and high-challenge collaborative learning sessions. *Metacognition and Learning*, *12*(2), 275–294. https://doi.org/10.1007/s11409-016-9167-5

Strauß, S., & Rummel, N. (2021). Promoting regulation of equal participation in online collaboration by combining a group awareness tool and adaptive prompts. But does it even matter? *International Journal of Computer-Supported Collaborative Learning*, *16*, 67–104. https://doi.org/10.1007/s11412-021-09340-y

Valsiner, J., Molenaar, P. C. M., Lyra, M. C. D. P., & Chaudhary, N. (Eds.). (2009). *Dynamic Process Methodology in the Social and Developmental Sciences*. Springer. https://doi.org/10.1007/978-0-387-95922-1

Volet, S., Vauras, M., & Salonen, P. (2009). Self- and social regulation in learning contexts: An integrative perspective. *Educational Psychologist*, *44*(4), 215–226. https://doi.org/10.1080/00461520903213584

Winne, P. H. (2010). Improving measurements of self-regulated learning. *Educational Psychologist*, *45*(4), 267–276. https://doi.org/10.1080/00461520.2010.517150

Winne, P. H. (2014). Issues in researching self-regulated learning as patterns of events. *Metacognition and Learning*, *9*, 229–237. https://doi.org/10.1007/s11409-014-9113-3

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). Mahwah, NJ: Lawrence Erlbaum. https://psycnet.apa.org/record/1998-07283-011

Winne, P. H., Nesbit, J. C., & Popowich, F. (2017). nStudy: A system for researching information problem solving. *Technology, Knowledge and Learning*, *22*, 369–376. https://doi.org/10.1007/s10758-017-9327-y

Wolters, C. A. (2003). Understanding procrastination from a self-regulated learning perspective. *Journal of Educational Psychology*, *95*(1), 179–187. https://doi.org/10.1037/0022-0663.95.1.179

Zheng, L., & Yu, J. (2016). Exploring the behavioral patterns of co-regulation in mobile computer-supported collaborative learning. *Smart Learning Environments*, *3*(1), 1–20. https://doi.org/10.1186/s40561-016-0024-4

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 13–39). New York, NY: Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7