



Examining socially shared regulation of learning in medical training: the interplay of heart rate change points on regulatory interactions

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Abstract

Socially shared regulated learning (SSRL) plays a crucial role in enhancing collaborative learning processes. This study explores the association between medical residents' team action, SSRL and heart rate changes using BioWorld, a technology-rich learning environment (TRE) designed to support medical practitioners' diagnostic reasoning skills as they solve a virtual patient case. A multimodal analysis approach was used to study the interactions between dyads as they solved patient cases. State lag sequential mining techniques were used to analyse these interactions. By leveraging multimodal data including logfiles and verbal data with physiological data, we analysed a total of 1398 events for the association between heart rate change point and team diagnostic actions, and 1432 events for heart rate change points and SSRL interactions. The findings indicate that heart rate change points serve as potential indicator signals for regulatory interactions and team actions. Furthermore, the investigation of heart rate change points and their association with SSRL interactions reveals a significant association with motivational interaction, highlighting the diverse roles of metacognitive, cognitive, emotional and motivational dimensions in SSRL. These findings carry practical implications for SSRL in medical education.

Keywords Socially shared regulated learning · Heart rate change point · Team action · Multimodal data · Lag sequential analysis

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Introduction

Team actions, the decisions and operations executed collaboratively, are crucial for achieving team success. However, without team members' joint efforts of adopting appropriate strategies, operations and regulations, team action alone may not necessarily lead to team success (Salas et al., 2005). This dynamic is particularly salient in high-stake decision-making processes such as clinical reasoning, where a single decision can lead to vastly different outcomes (Djulgovic et al., 2018). The effectiveness of team decision-making is closely connected to socially shared regulation of learning (SSRL), a framework that highlights the collaborative management of learning processes as pivotal to improving decision-making outcomes.

Self-Regulated Learning (SRL) theory provides a foundation for understanding complex learning processes, outlining loosely sequenced and cyclical phases of learning that requires continuous monitoring and adaptation of learning strategies (Winne & Hadwin, 1998; Zimmerman, 2002). Research has found that SRL strategies could affect and be affected by individuals' emotions (Authors; Li et al., 2021). While SRL primarily emphasises individual learning, SSRL extends this framework to teamwork contexts, where joint metacognitive, cognitive, behavioural and motivational states shape team dynamics and outcomes (Hadwin et al., 2017). SSRL refers to a deliberate, strategic and interactive process in which group members jointly plan, implement, reflect on and adapt their approach to a task, while actively sharing their metacognitive, cognitive, emotional and motivational processes (Järvenoja et al., 2025; Xu & Lou, 2024). Research has shown that SSRL can influence college students' SRL in online environments through the mediating role of motivational factors such as task value. In turn, online SRL has found to significantly predict school performance (Liu & Ye, 2025). However, emotions inevitably arise during social interactions and can significantly impact these regulatory processes. Such emotional responses are often observable through physiological indicators such as heart rate variability (Kreibig, 2010).

Understanding the interplays of team actions, SSRL interactions and physiological emotional responses such as changes in heart rate could provide valuable insights for better understanding and explaining team dynamics in complex problem-solving tasks. Emotional and physiological responses, as indicated by changes in heart rate, can relate to regulative processes and team dynamics (Kwon et al., 2014), ultimately impacting the effectiveness of collaborative efforts. Yet, the mechanism underlying these interconnections remain underexplored. Emotional responses and their physiological markers, such as heart rate changes, provide valuable insights for addressing this gap. By integrating multimodal data analysis, including behavioural and physiological indicators, can provide deeper insights into the complex interplay of team dynamics and decision-making (Järvelä & Hadwin, 2024; Järvelä et al., 2020). Our aim of this study is to understand how these physiological emotional arousals relate to team actions and SSRL interactions. Specifically, we address two research questions (RQs) to achieve our goal.

RQ1. How do team diagnostic actions relate to their heart rate change points in the computer-supported diagnostic task?

RQ2. How are different SSRL interactions related to heart rate change points when team members collaborate in the computer-supported diagnostic task?

Theoretical background

Socially shared regulation of learning (SSRL) in teamwork contexts

Drawing from self-regulated learning theory (SRL), the regulation of learning is an intentional, goal directed, metacognitive activity where learners strategically control their actions, thinking and beliefs towards the completion of a task (Zimmerman & Schunk, 2011). Socially shared regulated learning (SSRL) extends the concept of regulation from an individual to a social perspective. It emphasizes the social influence on collaborative learning, where group members collectively regulate their behaviour, cognition, emotions and motivation in a synchronized and productive manner (Järvelä et al., 2016a, b). It involves metacognitive and adaptive mental processes negotiated and fine-tuned in collaboration (Isohätälä et al., 2017). Key aspects of SSRL include meta monitoring of cognitive, motivational and emotional knowledge constructed about collaborative learning processes, such as negotiating and aligning representations of task requirements and goals (Järvelä et al., 2015). Cognitive processes are fundamental to collaborative learning, as they involve learners actively engaging in goal-directed thinking, reasoning and discussion to construct knowledge (Li et al., 2024). These cognitive interactions help synchronize group objectives, ensuring that members align their learning strategies and methods, thereby fostering coherence in collaborative efforts. However, cognitive processes do not operate in isolation; they are deeply intertwined with metacognitive regulation, where learners' awareness and control over their own learning strategies. A recent literature review on SSRL studies highlights that there are more frequently focuses on metacognitive aspects, such as interventions that promote learners' strategies for orienting, monitoring and regulating decision-making related to task goals or collaboration processes, followed by behavioural and cognitive dimensions than motivational and emotional aspects (Sharma et al., 2024). However, the dynamic interplay between these interactions and the long-term evaluation of acquired skills remains understudied.

In teamwork settings, social-emotional interactions can affect team members' cognitive processes, collaboration satisfaction and performance outcomes (Huang & Lajoie, 2024). While individuals' self-experienced emotions can influence their socio-cognitive processes, a team's socio-cognitive processes are also influenced by the partner's positive activated emotions (Avry et al., 2020). In medical teams, socio-emotional and metacognitive interactions were found to be highly correlated (Lajoie et al., 2015).

Motivation is embedded within the social, shared and interactive processes of learning (Järvelä et al., 2010; Schunk & Zimmerman, 2007). Recent studies have differentiated motivational interactions from socio-emotional ones to identify specific situations in socially shared regulation. For example, Näykki and colleagues (2014) identified motivational interaction as expressions of interests, goals and commitments, while socio-emotional interactions refer to relational interactions where emotions are aroused, or relational conflicts arise. As suggested by the SSRL framework, it is crucial to differentiate among emotional, motivational, cognitive and metacognitive interactions due to their practical implications. To unravel the complex mechanisms underlying medical teamwork, it would be valuable to delineate socio-motivational and socio-emotional layers, as well as meta- and socio-cognitive interactions by integrating multiple data sources. The dimensions of regulated learning mentioned above are dynamically changing and influencing each other, leaving room for investigation into why and how these interactions occur and their impact on team members' responses. As advocated by Authors, considerably more work

needs to be done to determine the synergistic nature of metacognitive, cognitive, emotional and motivational processes in learning regulation.

To fully optimize collaborative learning, it is essential to recognize the interconnected nature of metacognitive, socio-cognitive, socio-emotional and socio-motivational interactions. Socio-cognitive interactions drive knowledge co-construction, while socio-emotional exchanges (e.g. trust, empathy) and socio-motivational factors (e.g. shared goals, engagement) sustain group cohesion and persistence. Distinct patterns in these interactions such as how metacognitive prompts enhance cognitive alignment or how emotional support mitigates conflict must be examined to understand their collective impact on learners' collaboration experience and learning outcomes.

Recent progress in multimodal data analysis methods and theoretical developments in SRL and SSRL research offer promising avenues for further exploration on the non-observable nature of these regulatory processes. Notably, Järvelä and Hadwin (2024) have introduced the theoretical framework of Triggers, which provides a basis for advancing multimodal SRL research. This framework conceptualizes trigger events as empirical markers that can be identified in multimodal data to indicate the regulation of cognition, motivation, emotion and behaviour. Building on this foundation, our multimodal study explores the potential of using changes in heart rate as indicators of regulatory triggers.

Multimodal data analysis for examining SSRL research in teamwork contexts

Recent SSRL research incorporated multiple data modalities in interpreting psychological phenomena such as emotions, socio-emotional interactions, motivational and cognitive aspects of learning in teamwork (Noroozi et al., 2020; Törmänen et al., 2022), and monitoring learners' behaviours for adaptation (Amarasinghe et al., 2019; D'mello and Graesser (2010)). Specifically, recent advancements in SSRL research have embraced the use of observable data, including video and audio recordings, to examine the phenomenon more directly (Dindar et al., 2019; Törmänen et al., 2021). Analysing multimodal data has been instrumental in shedding light on the dynamics of SSRL, providing valuable insights into the perceptions and self-assessments of learners engaged in collaborative tasks. This shift acknowledges the complexity of SSRL, which encompasses not only observable interactions but also the internal cognitive and emotional processes that are challenging to measure directly (Authors). Furthermore, discourse analysis in computer-supported collaborative learning contexts enables the capture of situational social, cognitive, emotional and motivational states from learners' transcriptions of dialogues or their written texts (Hernández-Sellés et al., 2019; Authors; Kovanovic et al., 2014). Additionally, the adoption of think-aloud protocols and log data from computer-supported learning environments represents a significant stride towards capturing the learners' thought processes and actions, offering a more objective lens through which to view SSRL (Azevedo et al., 2011; Perry & Winne, 2012; Winne et al., 2006; Authors).

Moreover, the exploration of physiological measures has opened new avenues for understanding SSRL. Recent studies have begun to investigate the role of physiological responses, such as electrodermal activity (EDA) and heart rate, as indicators of the emotional and cognitive states underlying collaborative learning processes (Ahonen et al., 2018; Haataja et al., 2018; Pijera-Díaz et al., 2018). Despite the growing interest in these psychophysiological measures, their application in the context of collaborative learning, and SSRL in particular, remains relatively unexplored (Pijera-Díaz et al., 2016; Sobocinski et al., 2022).

Physiological data, such as heart rate variability, offers a promising yet underutilised metric for assessing emotional and cognitive engagement in learning contexts. Heart rate variability has been recognized for its potential to reflect the autonomic nervous system's responses to various emotional states. For instance, studies have shown that heart rate increases significantly in response to anger or fear, while it decreases during disgust (Kreibig, 2010). Similarly, Britton and colleagues (2006) found that heart rate during happy emotional states was lower compared to a neutral mood, highlighting the potential of heart rate measures to indicate emotional changes. Building on these foundations, the current study seeks to integrate physiological data, specifically heart rate, with video and log data analyses to investigate SSRL within the context of medical teams engaged in collaborative diagnostic tasks.

Heart rate change points in SSRL

The exploration of heart rate (HR) changes as a physiological marker in team decision-making and collaborative learning, particularly within the context of SSRL, is grounded in the premise that physiological responses offer a window into the underlying emotional and cognitive processes that drive collaborative interactions. Heart rate variability (HRV), as an indicator of autonomic nervous system activity, provides insights into the arousal and engagement levels of individuals in a group setting, reflecting their emotional responses to various stimuli and challenges encountered during collaborative tasks (Kreibig, 2010; Sobocinski et al., 2022). HRV focuses on the variability between heartbeats to assess autonomic nervous system function and overall cardiovascular health, whereas heart rate change points look at specific moments where the heart rate significantly increases or decreases, providing insight into acute physiological or emotional responses.

In the context of SSRL, where teams collectively regulate their learning processes, emotional and cognitive engagements are critical for effective joint decision-making and adaptation to evolving task demands. HR changes among team members can signal the alignment of emotional states and cognitive efforts, facilitating a more coordinated and coherent group regulation process (Pijeira-Díaz et al., 2018; Pijeira-Díaz et al., 2019). This rationale posits that monitoring HR changes offers a novel and objective measure to assess the dynamics of SSRL, providing empirical evidence to understand how teams navigate the complexities of collaborative learning environments and make joint decisions that propel their learning forward.

Analysing multimodal data enables us to calibrate events and features in the same environment and helps us to understand a full picture of how these reactions relate to each other. By incorporating multimodal data and using a sequential mining technique, we investigate how HR change points are related to team decision-making behaviours throughout medical team performance in the collaborative diagnostic task; and HR change points are related to medical team's SSRL interactions in the technology-enhanced learning environment.

Methods

Participants

The participants consisted of twelve medical residents enrolled in a professional development program at a large North American University. Upon approval from the

course instructor, all participants volunteered to undertake a collaborative diagnostic task as part of a field trip focused on teaching and researching clinical reasoning. Among the participants, eight were female and four were male, with an average age of 28.58 years ($SD=2.84$). In this study, we selected four groups consisting of eight female students who have similar levels of clinical experience for analysis. The study was conducted after receiving the approval from the ethics board of the institute where participants were involved.

Learning platform and procedure

The study consists of three stages, totalling two and a half hours: stage 1 involves the instructor's introductory remarks, stage 2 entails a diagnostic case-solving task using BioWorld, a learning platform for practicing medical reasoning skills, and stage 3 consists of the instructor's debriefing on the case. Data collection occurred during stage 2. Participants were seated in dyads in front of a single computer in a laboratory setting to discuss an assigned patient case and collaboratively make team decisions.

In this study, we used BioWorld (Lajoie, 2017; Huang et al., 2025) as the learning platform for the collaborative diagnostic task. Specifically, BioWorld is designed to support the development of clinical reasoning skills among medical practitioners by simulating a wide range of diagnostic cases with varying levels of complexity. These include simpler conditions, such as diabetes (the Amy case), and more complex scenarios, such as the Sam case. For the present study, we selected the Cynthia case (Pheochromocytoma) because its difficulty level was best aligned with the expertise and learning objectives of our participants.

The interface of BioWorld is shown in Fig. 1. It features four functions: Patient Case, Tests, Library and Hypotheses, displayed on the left-side bar. Learners could highlight specific symptoms deemed crucial for diagnosis in the provided patient profile. Within the Tests function, learners could search for and order diagnostic tests for the virtual patient, with results instantly displayed upon ordering. The Library function provided additional resources for learners to search and verify uncertain information regarding specific diagnoses. In the Hypotheses function, learners selected and evaluated each piece of evidence for hypotheses related to specific diagnoses, indicating support with a blue thumbs-up or lack

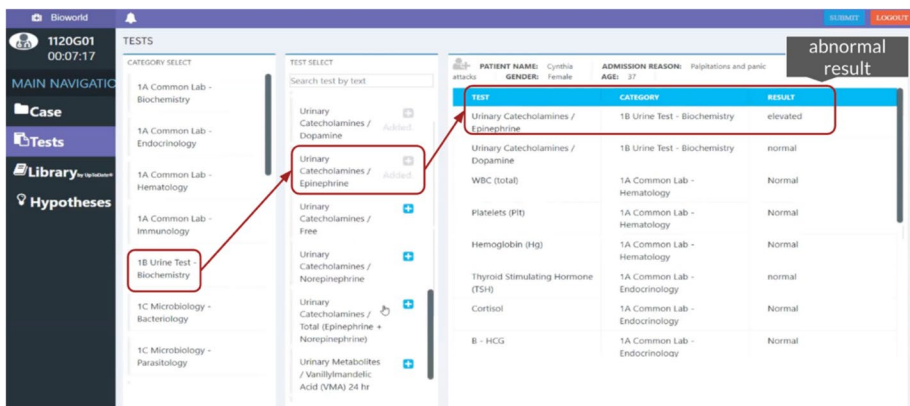


Fig. 1 The BioWorld Interface for the collaborative diagnostic task

of support with a red thumbs-down, and ranked them based on the test results. Learners had the flexibility to navigate between these functions at any time, facilitating collaborative problem-solving. For the final submission, learners selected one hypothesis for the diagnosis, confirming selected information from the patient case and test results. Upon submission, learners received a report comparing their diagnosis with an expert's diagnosis. The correct diagnosis for the task was Pheochromocytoma, a rare, usually benign tumour in an adrenal gland (Pacak et al., 2007).

Before the task began, each participant was assisted by one researcher to wear the Empatica E4 bracelet, a non-intrusive, watch-like device designed to capture learners' physiological signals on their non-dominant hand. In this study, the average heart rate was extracted from the raw blood volume pulse (BVP) signal, with a default sample rate expressed in 1 Hz. To ensure a fully automatic collaborative environment, dyads determined which individual would control the mouse and when to initiate the task. Throughout the task, screen and audio recording embedded in the lab computers were activated to capture each team's collaborative process and synchronize with logfiles and physiological data. The average task completion time of the selected dyads is 28.78 min ($SD = 12.47$), resulting in a total of 1.92 h of screen recording for transcription and analysis for this study.

Data processing and analyses

To achieve our goals, multimodal data sources were collected and analysed in this study. Data from logfiles were extracted to interpret team actions as behavioural data, while transcribed dialogues served as verbal data to interpret socially shared regulated learning (SSRL) interactions. Additionally, we collected physiological data, specifically heart rate, from which we calculated heart rate change points to investigate the signals for SSRL. Previous studies have identified physiological data, including electrodermal activity (EDA) (e.g. Authors) and heart rate (e.g. Sobocinski et al., 2022), as potential indicators of regulatory behaviours. Furthermore, the content of dialogue where significant sequences on SSRL interactions and heart rate change points were identified serve as a supplemental source to provide additional insights into our findings.

Qualitative content analysis on behavioural data—team diagnosis action from Logfiles

Team diagnostic actions are directly stored in BioWorld's logfiles. Given the reciprocal nature throughout the team decision-making processes and the flexibility in navigating through different interfaces on BioWorld, we coded each team action according to the three phases (i.e. forethought, performance, reflection) in Zimmerman (2002)'s SRL theory. A similar approach has been applied in previous studies to analyse logfiles data from BioWorld (e.g. Authors). This theoretically grounded model enables us to trace the unfolding of regulatory processes through observable actions and serves as the analytical foundation for identifying sequential patterns of regulation during collaborative problem-solving. Specially, it allows us to interpret the decision-making process in relation to key physiological indicators (e.g. heart rate change points). Table 1 summarizes the codes related to team actions in logfiles. Collect evidence items (CE) refers to learners' highlighting important information on the given patient protocol, and it is put in the forethought regulated learning phase as its initiation of task understanding. In the performance phase, the team action includes to order a new test for the virtual patient (add test: AD), search the library for information (SI) using the Library function in BioWorld, and select and rank hypotheses to

Table 1 Team diagnostic action extracted from the Logfiles

Phase	Team action	Acronym	Area in logfile
Forethought	Collect evidence items	CE	Case
Performance	Add test	AD	Test/chart
	Search the library for information	SI	Library
	Raise/manage hypothesis	MH	Hypotheses
Reflection	Categorize and link evidence/results	LR	Hypotheses
	Prioritize evidence/results	PR	Hypotheses
	Summarize for final diagnosis	SD	Submission
Others	Other actions related to task execution	TE	Navigation

generate potential diagnosis (raise/manage hypothesis: MH). In the reflection phase, learners evaluate their diagnostic performance by linking the obtained evidence with existed hypothesis (categorize and link evidence/results: LR), ranking the levels of importance of these evidence (prioritize evidence and results: PR) and summarizing a final diagnosis report to submit (summarize for final hypothesis: SD). In addition to the codes that have meaning in functions related to regulated learning, TE (short for task execution) is coded as 'Others' when the mouse was navigating across the interface and switching between functions provided by the learning platform.

Qualitative content analysis on SSRL interactions from verbal dialogue

To interpret SSRL interactions, verbal data was extracted from the team's dialogues, as these provide insights into micro-level interactions that may not be captured in logfiles. Participants' information was de-identified throughout the analysis; for example, we use identifiers such as P1 and P2 for individuals and G1 and G2 for groups. The dialogue from the task was transcribed using Whisper, an automatic speech recognition (ASR) system (Open AI, 2023), and subsequently coded by two researchers. The transcriptions were analysed at the meaningful unit, defined as a complete utterance or a meaningful segment within it. Each meaningful unit was assigned one or two codes corresponding to the interaction types, as one utterance could reflect more than one interaction type. The principal researcher adapted an SSRL coding scheme for the medical diagnosis context, incorporating metacognitive, cognitive, motivational and socio-emotional interactions (see Järvelä et al., 2016a, b; Näykki et al., 2014; Authors). Specially, reflection is categorized under the socio-cognitive dimension within the medical diagnostic context as it primarily involves task-focused self-evaluation and group performance discussions. These reflective moments are less about strategic planning or monitoring (core aspects of metacognition) and more about shared cognitive assessment of what has been completed and what remains to be done. Similarly, activating prior knowledge is treated as a cognitive process because it appears in discourse when team members share relevant clinical experiences or factual knowledge to advance the task. This is understood as a form of knowledge exchange rather than a metacognitive function like planning or orientation. In contrast to individual prior knowledge activation often used in metacognitive planning (e.g. Li et al., 2022a, b), these team-based activations are grounded in collaborative reasoning and are directly task-oriented.

Table 2 Coding Scheme for SSRL interaction in the collaborative diagnostic task

SSRL layer	Sub-layer	Full code	Code	Description	Sample quote
Metacognitive interaction	Metacognition	Metacognitive strategy	Meta	Students' discussion targeted their cognitive progress	So anything else that we forgot? Uh do we like to randomize things?; Okay. Do you have any differential in mind?; So let's just see what they find in the urine. Make sure that this is what we are
Socio-cognitive interaction	Forethought	Task understanding	TU	Students verbally monitor their task understanding by expressing their understanding or lack of understanding about the task	(Commented on the tests options) That's very wide range; Wait, but when I'm doing this, oh, I have to add it somewhere
		Task planning	TPPL	Students discussing about the plan or strategy to complete the task	Do you wanna highlight staff?; Should we read it (the patient case) together?
	Performance	Prior knowledge activation	PKA	Students sharing previous diagnostic experience that are relevant to the given patient profile or linking information from the patient protocol with their clinical knowledge	And then in terms of things that can be caused like often if you're treating high blood pressure, then you would have more symptoms of like orthostatic hypotension. So I'm wondering if it's like comfortably unrelated. We had a case of field chromosome
	Content understanding		CU	Students discussing about the task information (including repeating patient information) for their following executive actions	(Murmuring the symptom of the patient) palpitations, sweating, flushing. Not triggered by any specific costs. Ten pounds, dizzy, cloudy
	Resources seeking		RS	Students seeking for external sources in the library that are helpful for task solution	Okay. So then, what do you think is going on? [Searching in the library] ...something in the adrenal glands? Okay, click

Table 2 (continued)

SSRL layer	Sub-layer	Full code	Code	Description	Sample quote
Socio-motivational interaction		Task progress	TPR	Students voicing out their perceptions of their progress towards task completion and their goals	If that's normal, we're not going to get it; So far, everything's normal (test order results)
	Reflection	Task reflection	TR	Students reflecting on the quality of the task solution, including evaluation of the test results, evidence rank for hypothesis, and overall performance. Students summarizing what the group has obtained	So the weight loss. I mean, it's rare to have type 1 that way; That's the only one that I would even think about. Another thing is given her – you could see if her heart is enlarged, but it's not going to really change anything. We do it chest X ray, right? Would we want to – Her beta-HCG is negative
	Feelings of motivation	Expression on goals, commitment	FoM	Students expressing about goals, commitment and interests towards the collaborative task/ findings	Oh, wow. I didn't even think they were... that they were, like, giving us the results. (Comment on the platform); (Complimented on the learning platform) This is so cool That up-to-date is linked to this
	Feelings of beliefs	Levels of belief on task completion	FoB	Students commenting on their beliefs about the ability to complete the task	(After searching for materials in the library) I think that's about it; (When summarizing the diagnostic result) Yes. You want them. And also the urine one

Table 2 (continued)

SSRL layer	Sub-layer	Full code	Code	Description	Sample quote
Socio-emotional interaction	Socio-emotional experiences	Sharing emotional experiences	SEE	Students sharing positive or negative feelings (e.g. expression of uncertainty) towards the task	We had a case of field chromosomes... it was very interesting; (With a tone of confusion) Looking for what?
	Explicit emotional responses	Joking and/or laughing	EER	Students joking and/or laughing together	Oh, somatic disorder. Very, very in mind. (LAUGH); Very raw differential. (LAUGH)
	Socio-emotional support	Support teammate emotionally	SES	Students expressing a good team spirit, praising the teamwork, or encouraging teammate	So wow such a good job; Yeah. Thank you. You learned so well at your clinic cases
	Task execution	Task execution	TE	Students executing actions including reading/highlighting task material, selecting tests, ranking hypothesis, writing report, asking researcher for information	And the treatment... [continued exploring library]; Pheochromocytoma (Start ranking the evidence for the hypothesis)

Adapted from Järvelä et al., 2023; Näykki et al., 2014; Authors

The adapted coding scheme with sample excerpts of SSRL interaction in the collaborative diagnostic task is summarized in Table 2.

Following a thorough investigation of the transcription and coding scheme, the two researchers independently coded the same pair of groups through 234 iterations of conversation. The interrater reliability for each interaction category exceeded 0.7 (metacognitive: 0.89, cognitive: 0.89, emotional: 0.77, motivational: 0.79, task execution: 0.83), meeting the criterion for Cohen's kappa (McHugh, 2012). The researchers individually coded the remaining groups after solving discrepancies. While the transcribed language itself conveys rich resources for interpreting learners' interactions throughout collaboration, triangulating with multiple data sources is ideal for depicting a fuller picture of the team diagnostic process.

Physiological data—heart rate change point

In this study, physiological data were analysed to identify significant changepoints in heart rate, which are indicative of shifts in emotional or cognitive states during collaborative learning tasks. To achieve this, a Bayesian changepoint detection algorithm, specifically the Bayesian Estimator of Abrupt change, Seasonal change and Trend (BEAST) as delineated by Zhao et al. (2019) was employed. This approach allows for the probabilistic identification of points in time where the heart rate demonstrates substantial changes, suggesting moments of increased or decreased physiological arousal related to the collaborative learning process. The analysis was carried out utilizing the RBeast library,¹ a comprehensive Python package designed for the application of the BEAST algorithm to time series data.

Specifically, heart rate change points are detected at the individual level where all significant individual change points detected during the task are included in the analysis. We examined the temporal alignment between individual CPs and team-level behavioural events (e.g. decision points, discourse patterns) to explore how physiological responses may reflect or co-occur with socially shared regulatory processes. This approach assumes that while the physiological data is inherently individual, the context in which those responses occur, such as shared task demands or emotionally charged moments in team discussions, can allow individual signals to serve as indicators of group-level dynamics. This is grounded in prior work that has linked individual affective signals to socially shared regulation and coordination in collaborative learning settings (e.g. Bakhtiar et al., 2018; Malmberg et al., 2019).

Lag sequential analysis

To investigate the sequential associations between heart rate change points and diagnostic team actions and SSRL behaviours, respectively, two-state lag sequential analyses (LSA) were performed. LSA allows one to determine significant sequential patterns among categorical variables, or so-called events (O'Connor, 1999).

For the LSA in our study, the change points of heart rate were input as events, as were the SSRL behaviours coded by researchers and team actions extracted from the logfiles. All the events from different data sources are synchronised in the same time frame using excel. For the association between heart rate change point and team diagnostic actions, a

¹ <https://pypi.org/project/Rbeast/>

total of 1398 meaningful events were logged at input for LSA; for the association between heart rate change point and SSRL behaviours, a total of 1432 meaningful events were logged. The term 'lag' indicates the relative position of a target event in relation to a given criterion event (Olson et al., 1994). For example, 'lag 1' signifies that the target event immediately follows the criterion event (direct transition), while 'lag 2' denotes the event positioned two steps ahead of the criterion event, and so forth (indirect transition). Specifically, we included both one consecutive lag (i.e. lag 1) and two consecutive lags (i.e. lag 2) for observations, as the criterion has been tested in previous studies within SSRL contexts (Authors; Malmberg et al., 2017).

We applied the 'LagSequential' package in R to calculate the transitional probabilities, chi-square, z-scores of adjusted residuals and Yule's Q values (O'Connor, 1999). After Pearson's chi-square test was significant for both frequency matrices, indicating that the associations between the events were not determined by chance (Bakeman & Quera, 2011), we further examined which of the associations between the two events were significant. This was done using indices including z-scores resulting from adjusted residuals, Yule's Q s and transitional probabilities among events at lags 1 and 2. Specifically, the transitional probabilities were calculated to determine the likelihood of whether a certain event would follow another (or the same) event. The z-scores resulting from adjusted residuals assessed whether these transitional probabilities significantly deviated from expected values. Meanwhile, Yule's Q , a transformation of the odds ratio to a $[-1 \dots +1]$ scale, was also employed to ascertain the strength of association in addition to the z-scores.

Results

RQ1. How do team diagnostic actions relate to their heart rate change points in the computer-supported diagnostic task?

To examine the association between heart rate change point and team diagnostic actions, we conducted a state lag sequential analysis. We summarize significant direct and indirect associations among heart rate change point and team diagnostic actions in Tables 3 (lag 1)

Table 3 Team diagnostic action with significant sequential lag states in lag 1

Events	Lag 1 event	Adjusted residuals	Yule's Q s	Transitional probabilities
CP	CE	2.26*	0.50	0.08
	SD	4.20*	0.75	0.08
	TE	4.93*	0.59	0.29
SI	CP	3.10*	0.53	0.13
MH	SD	4.78*	0.79	0.09
SD	CP	7.33*	0.87	0.38
	PR	6.06*	0.84	0.29
TE	CP	3.70*	0.49	0.11
	SI	2.18*	0.34	0.08

CP the change point of heart rate, CE collect evidence items, SI search the library for information, MH raise/manage hypothesis, PR prioritize evidence/results, SD summarize for final diagnosis, TE task execution.

* indicates $p < .05$.

Table 4 Team diagnostic action with significant sequential lag states in lag 2

Team action	Lag 2 event	Adjusted residuals	Yule's Q s	Transitional probabilities
CP	CE	3.75*	0.64	0.11
	SD	4.35*	0.75	0.08
	TE	3.29*	0.46	0.23
SI	CP	4.32*	0.63	0.16
	TE	3.84*	0.51	0.25
SD	CP	5.42*	0.81	0.30
	PR	3.87*	0.75	0.20
PR	SD	3.87*	0.73	0.08
TE	SI	6.34*	0.67	0.15
	MH	2.33*	0.38	0.07

and Table 4 (lag 2). A chi-square test confirmed a significant relation between the rows and columns of the tallied frequencies ($\chi^2 = 3193.77$, $df = 64$, $p < .0010$, Monte Carlo 2-sided). The visualization of the association among events is shown in Fig. 2, along with all significant z-scores of adjusted residuals and Yule's $Q > 0.3$. Specifically, a z-score greater than 1.96 indicates that the transition between two behaviours is statistically significant (i.e. $p < .05$) (Bakeman & Quera, 2011). In total, 9 direct and 10 indirect transitions met the significant criteria.

As depicted in Fig. 2, heart rate change point has significant associations with various team actions at all stages of regulated learning (e.g. forethought: CE, performance: SI, reflection: SD). Specifically, it serves as an integral junction for team actions, as evidenced by significant direct transitions such as CP to TE, SD to CP.

Interestingly, both direct and indirect transitions between heart rate change points and summarizing for the final diagnosis at the reflection stage (CP to SD: $z = 4.20$, $Q = 0.75$, $Z_{lag2} = 4.35$, $Q_{lag2} = 0.75$; SD to CP: $z = 7.33$, $Q = 0.87$, $Z_{lag2} = 5.42$, $Q_{lag2} = 0.81$) suggest that

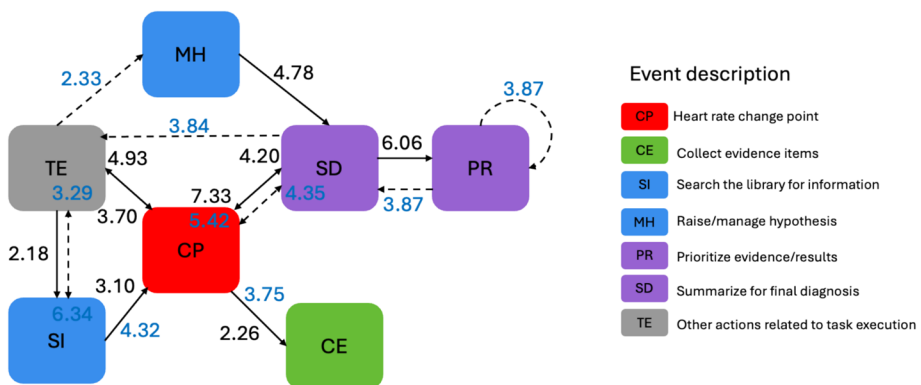


Fig. 2 Significant transitions between the events of team diagnostic actions and the change point of heart rates. *Note.* All significant direct and indirect transitions (i.e. those with a z-score greater than 1.96, $p < .05$) are illustrated in the graph. Solid lines indicate direct transitions with z-scores in black, dotted lines indicate indirect transitions with z-scores in blue

Table 5 SSRL interactions with significant sequential lag states in lag 1

SSRL interaction	Lag 1 event	Adjusted residuals	Yule' s Qs	Transitional probabilities
TPL	TE	2.33	0.25	0.22
PKA	SES	2.75	0.35	0.14
META	FoM	2.21	0.58	0.04
SEE	SES	2.32	0.33	0.13
	FoM	2.67	0.55	0.04
FoM	EER	2.62	0.65	0.17
	RS	2.97	0.75	0.11
RS	TPL	2.32	0.48	0.23

TPL task planning, *PKA* prior knowledge activation, *META* metacognitive interaction, *SEE* socio-emotional experiences, *FoM* expressions of motivation, *RS* resources seeking, *TE* task execution, *SES* socio-emotional support, *EER* explicit emotional responses

Table 6 SSRL interactions with significant sequential lag states in lag 2

SSRL interaction	Lag 2 event	Adjusted residuals	Yule' s Qs	Transitional probabilities
CP	FoM	2.52	0.63	0.05
TPL	TPR	2.20	0.34	0.09
PKA	SEE	2.62	0.33	0.14
SES	FoB	2.43	0.37	0.11
META	TR	2.37	0.36	0.16
TR	FoM	2.06	0.51	0.03
FoM	META	2.21	0.58	0.17
	EER	2.62	0.65	0.17

CP The change point of heart rate, *TPL* task planning, *PKA* Prior knowledge activation, *SES* socio-emotional support, *META* metacognitive interaction, *TR* task reflection, *FoM* expressions of motivation, *TPR* task progress, *SEE* sharing emotional experiences, *FoB* feelings of beliefs, *EER* explicit emotional responses

residents can largely control their emotional variability until the very last stage of the task when the final diagnosis is formed. The finding aligns with neuroscience research indicating that activation of the cognitive division in an adjacent area of the anterior cingulate cortex tends to deactivate the affective dimension, and vice versa (Bush et al., 2000). Such insights reinforce existing studies in medicine emphasizing the importance of medical professionals' emotional regulation throughout the diagnostic process (Lajoie et al., 2015; Kazemitabar et al., 2019).

RQ2. How are different SSRL interactions related to heart rate change points when team members collaborate in the computer-supported diagnostic task?

Likewise, a chi-square test in another state lag sequential analysis confirmed a significant relation between the rows and columns of the tallied frequencies ($\chi^2=696.07$, $df=196$,

$p=0$, Monte Carlo 2-sided). Tables 5 and 6 illustrate significant transition state values between SSRL interaction events and the change point of heart rate in lag 1 and lag 2.

Notably, significant self-loop SSRL events are not displayed in the table, as most of them are significant (z -values > 1.96 , Yule's $Q > 0.30$), with exceptions including heart rate change points, metacognitive interaction and sharing emotional experiences of socio-emotional interaction. The reasons for the non-significant self-loop states of heart rate change points and metacognitive interactions are similar; they function more towards reacting or transitioning to other interactions. For instance, metacognitive interaction directs towards cognitive action, while heart rate change points may be associated with motivational and emotional interactions. Furthermore, unlike laughing or joking, which could lead to subsequent chains shared among team members, sharing emotional experiences with a partner could signify a need for team efforts to monitor or regulate the current situation, potentially leading to other types of interactions. In total, 8 direct and 8 indirect transitions met the significant criteria as shown in Fig. 3.

Apart from self-loops, direct transitions appear to occur more frequently between the same type of socio-interactions (e.g. resources seeking-task planning, sharing emotional experiences-providing emotional support). Socio-motivational interaction, particularly the expression of feeling of motivation, plays a significant role in connecting to all three other types of interactions: metacognitive interaction-feeling of motivation ($z=2.21$, $Q=0.58$), feeling of motivation-cognitive interaction (resources seeking, $z=2.97$, $Q=0.75$), feeling of motivation-socio-emotional interaction (explicit emotional responses, $z=2.62$, $Q=0.65$). Additionally, the multiple significant associations between socio-motivational and socio-emotional interactions (e.g. SEE to SES, $z=2.32$, $Q=0.33$; SES to FoB, $z_{\text{lag}2}=2.43$, $Q_{\text{lag}2}=0.37$) highlight a strong linkage between these two types of interaction in our diagnostic problem-solving context. This finding aligns well with previous findings in collaborative problem settings, which emphasize the close nature of these interactions (Järvelä et al., 2016a, b).

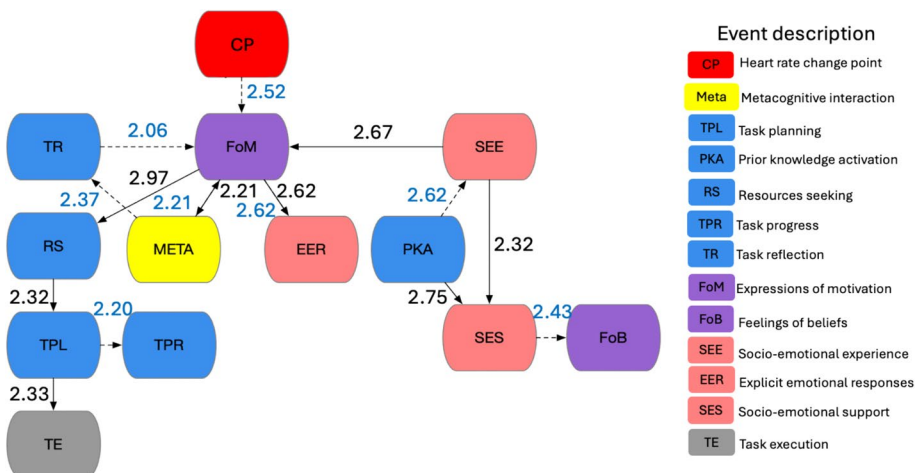


Fig. 3 Significant transitions between the events of SSRL interactions and the change point of heart rates. *Note.* Dotted lines indicate indirect transitions with z -scores in blue. Yellow: metacognitive interaction; blue, socio-cognitive interaction; purple, socio-motivational interaction; orange, socio-emotional interaction; grey, task execution

Notably, there is a significant indirect transition from heart rate change points to socio-motivational interaction regarding expressions of goals, commitment and interests ($z_{lag2}=2.52$, $Q_{lag2}=0.63$), as well as indirect transitions from feeling of motivation to metacognitive interaction ($z_{lag2}=2.21$, $Q_{lag2}=0.58$), and feeling of motivation to explicit emotional responses ($z_{lag2}=2.62$, $Q_{lag2}=0.65$).

One sample scenario regarding heart rate change point and motivational interaction is when G1P2 shared her prior experience, followed by P1's heart rate change point upon expressing satisfaction of obtained knowledge and in support of her partner. This sequence illustrates how physiological arousal aligns with motivational interaction, fostering a positive team climate conducive to team cohesion. Similarly, G4P1 experienced a heart rate change point while searching for resources and found the targeted information: 'What's the presentation (of the diagnosis)? Okay.' [RS, CP]. Followed by socio-emotional and motivational interactions with G4P2, who commented on the enjoyable experience: 'It's kind of fun (commenting on the platform). [Laugh]' [SEE, FoM]. The interaction was further followed by G4P1's explicit emotional expression: '[Laugh] Yeah.' This further highlights the association between heart rate change points and socio-motivational interaction, emphasizing the role of physiological signals in shaping team engagement.

Furthermore, the dialogues reveal associations between heart rate change point and metacognitive interaction within dyads. For instance, in group 1, P2 experienced a heart rate change point while engaging in metacognitive interaction by asking her partner about specific aspects of the task: 'Is there anything specific we should look at? What do you think? I don't think we did actually. I can't really blank it on what it stands (for). I saw maybe it's here' [META]. Similarly, in group 2, P1's metacognitively reflection on their current observation of a certain type of test related to the case triggers a heart rate change point in P2, indicating the influence of metacognitive interaction on physiological responses. These sequential patterns signify the interconnectedness of heart rate change points and metacognitive interactions in team dynamics, shedding light on the intricate mechanism underlying problem-solving tasks.

These specific sequences lend further credence to our hypothesis, indicating heart rate change points as a potential measure for socio-motivational and socio-emotional interactions. It also suggests that metacognitive interactions may precede physiological signals in team members, underscoring the importance of considering these aspects in understanding collaborative dynamics in medical diagnosis teamwork.

Discussion

Our study investigates the dynamic processes of teamwork during a medical diagnostic task through the lens of SSRL. Teamwork during a medical diagnostic task has been recognized as an essential aspect in doctor training (Lerner et al., 2009; Marlow et al., 2016; Wright et al., 2009). Through negotiating, sharing prior knowledge and monitoring team progress, team members make decisions collaboratively. Accordingly, SSRL (Järvelä & Hadwin, 2013) has appeared as a valuable theoretical framework for examining teamwork in medical diagnostic tasks, offering insights that can enhance learning outcomes. By examining team decision-making behaviours, metacognitive processes and cognitive, motivational and emotional interactions related to heart rate change points in this diagnostic task, we gain insights into how medical professionals collaborate in authentic situations to save a patient's life. In addition to the integration of this theoretical foundation with

changes in heart rate detected during medical teamwork, we present an empirical application of multimodal data analysis in response to the rapid evolution of digitalization (Järvelä & Hadwin, 2024) for educational psychology research. Additionally, by analysing physiological data signals from heart rate change points and their sequential association with team behaviours and SSRL interactions, we identify heart rate change points' function as an integral junction for team diagnostic actions, and its significant association with socio-motivational interactions. These findings have theoretical and methodological implications for future directions.

This study contributes to the understanding of medical teams' collaborative decision-making by examining the relationship between heart rate change points and decision-making behaviours. While prior research has extensively explored the role of peer feedback in medical education, demonstrating that high-quality peer evaluations enhance learners' work quality, confidence and professional behaviour (Lerchenfeldt et al., 2019), there remains a gap in investigating more nuanced or less observable aspects of peer interactions, particularly in autonomous team settings. Our work addresses this gap by analysing physiological and behavioural data to uncover deeper insights into team dynamics during SSRL. Recent research has indicated potential links between transitions in heart rate and shifts in group metacognitive activity, characterized by adaptive, maladaptive and on-track sequences during collaborative learning (Sobocinski et al., 2020). Nevertheless, there are several calls for additional empirical work to confirm the relationship between physiological activities and SSRL for theoretical advancement in the field of regulated learning (Moreno et al., 2024; Authors; Sobocinski et al., 2020). By examining physiological responses alongside team dynamics, the research sheds light on how physiological states impact collaboration and decision-making in healthcare, offering insights for improving teamwork efficiency and outcomes. Through analysis of team actions extracted from logfiles, we identify sequential patterns between team decision-making behaviours and heart rate change points. Notably, significant associations are observed between heart rate change points and all three phases of regulated learning in team actions, with particularly strong direct and indirect linkages observed during the reflection phase of team diagnosis. These physiological behaviour patterns suggest that emotional shifts serve as visible markers of deeper regulatory processes in medical teamwork. These findings offer practical implications for medical practice and training. First, while traditional assessments emphasize structured peer evaluations or diagnostic outcomes, our results reveal that the quality of team interactions (e.g. how team members negotiate uncertainty or support each other during HR instability) may serve as a stronger indicator of long-term team competency. For example, teams that maintained stable HR during conflict (indicating emotional regulation) were more likely to engage in constructive reflection, resulting in both improved diagnostic accuracy and operational efficiency (Huang et al., 2025). Second, our study supports the ongoing call for process-oriented professionalism assessment (Sharma et al., 2024) by demonstrating that professional competence should be evaluated not just through final outcomes, but through the quality of internal team dynamics. The integration of log data with HR monitoring provides tangible metrics for assessing interaction quality, such as how teams adapt strategies following physiological markers. Additionally, our data show that most medical professionals maintain strong emotional control during diagnosis, as evidenced by limited HR fluctuations during the task. Nevertheless, training on emotion management such as coping strategies on stress are still necessary in such high cognitive and emotional demanding field. For instance, incorporate HR biofeedback in team debriefs can help teams recognize how emotional states impact decision-making.

Furthermore, our investigation into medical teams used a micro-lens to examine meta-cognitive, socio-cognitive, socio-emotional and socio-motivational behaviours during real-time interactions within the SSRL framework. The significant association between heart rate change points and socio-motivational interactions underscores the potential of physiological signals to inform interpretations of subsequent interactions in the collaborative process. This distinction has practical value: while emotions are often transient, motivational expressions are more predictive of task persistence and coordination, making them critical targets for instructional interventions. Designing prompts or training scripts that foster motivation-enhancing behaviours (e.g. goal reaffirmation, peer encouragement) may thus improve team resilience, especially during high-pressure tasks.

Additionally, our differentiation between socio-motivational from socio-emotional interactions in relation to physiological signals offers novel insights, as does the identification of reciprocal sequential patterns between expressions of motivation and metacognitive interactions, shedding light on the inner mechanism of SSRL in diagnostic tasks. These patterns suggest a mechanism through which motivation can spark metacognitive engagement, or vice versa, indicating points where team dynamics can be scaffolded to maintain momentum or redirect effort. For example, when motivation dips (evidenced by physiological signals or silence), prompting learners to articulate goals or plans may re-engage both emotional and cognitive resources. Moreover, these insights are grounded in the temporal dynamics of regulatory phases. Motivational and metacognitive exchanges often clustered around critical transitions (e.g. between problem stages or after errors), which aligns with Zimmerman's (2002) model of forethought, performance and self-reflection phases. This pattern is also supported in SSRL literature, where regulatory activity including socio-motivational scaffolding and metacognitive planning, is shown to intensify during task transitions or regulatory breakdowns (Hadwin et al., 2017; Järvelä et al., 2016a, b; Malmberg et al., 2017). Understanding when these regulatory shifts occur in real time offers educators the opportunity to design phase-specific interventions such as motivational check-ins during task initiation or reflective prompts at task conclusion to better align support with learners' regulatory needs.

By employing a multimodal approach that integrates physiological data with behavioural observations, this study extends current understanding of how different dimensions of social interactions are associated with internal, often unobservable, emotional responses during collaborative learning. This integration enables a more holistic view of learners' regulatory processes and emotional states in context. Our method also answers ongoing calls to model the temporal process of collaborative learning, emphasizing how regulation unfolds and is embedded in team dynamics (Authors). Building on this, and as suggested by Winne (2015), the state of art in advancing SSRL studies lies in leveraging data mining techniques, such as process and sequence mining, to better capture the complexity of regulation over time. By applying state lag sequence analysis to both heart rate change points and medical team behaviours, our study contributes to a deeper, more structured understanding of clinical reasoning processes. This analytical approach illuminates the sequential dependencies between physiological signals and team actions, facilitating nuanced insights into when and how regulation occurs within the ebb and flow of collaborative problem-solving.

Limitations and future direction

With the support of an advance computational technique capable of identifying complex patterns in physiological time series data, our study incorporated multiple data sources to depict the unobservable nature of interactions and physiological responses that are challenging to capture in real-time practice. Although research with smaller sample sizes is acceptable in research within medical contexts (e.g. Moreno et al., 2025), and the richness of conversational data combined with multimodal analytics in this study provides sufficient depth to support the findings, the limited and gender-homogenous sample may restrict the generalizability of our results due to potential gender biases in emotional regulation and teamwork. Future research using similar methods should aim to include larger and more gender-diverse samples to strengthen the generalizability of the findings. Furthermore, as the conversation is based on interactions within a simulated medical diagnostic context using a single patient case, it may not fully reflect real-world clinical decision-making scenarios, especially in cases with different levels of complexity. Additionally, the findings may not be applicable in other contexts, as medical residents tend to be more capable in managing emotional arousals. For example, in other contexts which have a higher demand for creativity, more frequent physiological changes could be detected throughout interactions (e.g. Fusaroli et al., 2016; Silvia et al., 2014). This study provides an empirical example for the multimodal design of SSRL research for education in health sciences. Further studies can investigate the role of heart rate change points in motivational regulation and shared regulation within other subject-specific domains.

This study revealed the sequential patterns of heart rate change points related to team decision-making behaviours and SSRL interactions. While these findings lay a foundation for understanding the dynamic regulation processes in teams, they should be interpreted with caution. First, although lag sequential analysis captures the order of events, it does not account for the actual time intervals between them. This means that a heart rate change point followed by a regulatory utterance several minutes later may not reflect a meaningful or immediate response, and such associations should be interpreted with caution. Second, we limited the analysis to two lags, which may have restricted our ability to detect longer-term dependencies or delayed regulatory patterns. As such, future studies could explore analytic approaches that incorporate temporality and broader lag windows to better capture the complexity of team dynamics and physiological responses over time. Future study may also consider designing tasks with different targets for interaction, such as co-regulation (CoRL), or a combination of CoRL and SSRL in the context of computer-supported collaborative diagnostic settings, to explore how these types of regulated interactions contribute to heart rate change points.

While this study provided evidence for triangulating physiological signals, behavioural and verbal data to recognize trigger events for team diagnostic behaviours and SSRL interactions, future work is needed to test different data signals and their conceptual alignment in explaining the theoretical phenomenon of regulation in medical diagnostic teamwork. In our study, we analysed team actions and SSRL interactions as general team behaviours without accounting for group differences. Future study could explore group differences in performance by conducting case studies. One approach is to complement current data sources by interviews, where participants provide explanations for their own engagement in the group dynamics from the socio-cognitive perspective (Järvelä et al., 2010). Adding analysis in such experimental data can elucidate learners' perceived experiences.

Conclusion

The study contributes to the advancement of SSRL research in medical education by exploring sequential patterns between team decision-making behaviours, and different types of SSRL interactions related to team members' physiological signals indicated by heart rate change points, aiming to inform SSRL in collaborative diagnosis. By effectively detecting heart rate change points among team members, regulatory prompts could be designed to promote higher level metacognitive processes in clinical reasoning and foster a positive team climate, ultimately enhancing team performance. This study presents an initial step in this direction by examining the association between potential physiological signals and team decision-making behaviours and interactions informed by SSRL. Subsequent studies endeavours could delve deeper into elucidating the intricate relationship between physiological signals and different SSRL interactions using computational techniques, thereby providing a more detailed depiction of their joint impacts on performance.

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Author contributions The study design, material preparation and data collection were performed by Xiaoshan Huang. The data analysis was performed by Xiaoshan Huang and Andy Nguyen. The first draft of the manuscript was written by Xiaoshan Huang and all the previous versions of the manuscript was reviewed and revised by all authors. All authors read and approved the final manuscript.

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Data availability Contact the corresponding author for data requests.

Declarations

Ethics approval and consent to participate The study was approved by the institutional review board of McGill University (#23–04–086), and informed consent was obtained from all individual participants included in the study.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

Disclaimer Any opinions, findings and conclusions or recommendations expressed in this paper, however, are those of the authors and do not necessarily reflect the views of the SSHRC and the FRQSC.

References

- Ahonen, L., Cowley, B. U., Hellas, A., & Puolamäki, K. (2018). Biosignals reflect pair-dynamics in collaborative work: EDA and ECG study of pair-programming in a classroom environment. *Scientific Reports*, 8(1), 3138. <https://doi.org/10.1038/s41598-018-21518-3>
- Amarasinghe, I., Hernández-Leo, D., & Jonsson, A. (2019). Data-informed design parameters for adaptive collaborative scripting in across-spaces learning situations. *User Modeling and User-Adapted Interaction*, 29(4), 869–892.
- Avry, S., Chanel, G., Bétrancourt, M., & Molinari, G. (2020). Achievement appraisals, emotions and socio-cognitive processes: How they interplay in collaborative problem-solving? *Computers in Human Behavior*, 107, Article 106267. <https://doi.org/10.1016/j.chb.2020.106267>

- Azevedo, R., Cromley, J. G., Moos, D. C., Greene, J. A., & Winters, F. I. (2011). Adaptive content and process scaffolding: A key to facilitating students' self-regulated learning with hypermedia. *Psychological Test and Assessment Modeling*, 53(1), 106–140.
- Bakeman, R., & Quera, V. (2011). *Sequential analysis and observational methods for the behavioral sciences*. Cambridge University Press.
- 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, 57–90.
- Britton, J. C., Taylor, S. F., Sudheimer, K. D., & Liberzon, I. (2006). Facial expressions and complex IAPS pictures: Common and differential networks. *NeuroImage*, 31(2), 906–919. <https://doi.org/10.1016/j.neuroimage.2005.12.050>
- Bush, G., Luu, P., Posner, M. I., Bush, G., Luu, P., Posner, M. I., Bush, G., Luu, P., & Posner, M. I. (2000). Cognitive and emotional influences in anterior cingulate cortex. *Trends in Cognitive Sciences*, 4(6), 215–222. [https://doi.org/10.1016/S1364-6613\(00\)01483-2](https://doi.org/10.1016/S1364-6613(00)01483-2)
- D'mello, S. K., & Graesser, A. (2010). Multimodal semi-automated affect detection from conversational cues, gross body language, and facial features. *User Modeling and User-Adapted Interaction*, 20(2), 147–187.
- Dindar, M., Alikhani, I., Malmberg, J., Järvelä, S., & Seppänen, T. (2019). Examining shared monitoring in collaborative learning: A case of a recurrence quantification analysis approach. *Computers in Human Behavior*, 100, 335–344. <https://doi.org/10.1016/j.chb.2019.03.004>
- Djulfbegovic, B., Elqayam, S., & Dale, W. (2018). Rational decision making in medicine: Implications for overuse and underuse. *Journal of Evaluation in Clinical Practice*, 24(3), 655–665. <https://doi.org/10.1111/jep.12851>
- Fusaroli, R., Bjørndahl, J. S., Roepstorff, A., & Tylén, K. (2016). A heart for interaction: Shared physiological dynamics and behavioral coordination in a collective, creative construction task. *Journal of Experimental Psychology: Human Perception and Performance*, 42(9), 1297.
- Haataja, E., Malmberg, J., & Järvelä, S. (2018). Monitoring in collaborative learning: Co-occurrence of observed behavior and physiological synchrony explored. *Computers in Human Behavior*, 87, 337–347. <https://doi.org/10.1016/j.chb.2018.06.007>
- Hadwin, A., Järvelä, S., & Miller, M. (2017). Self-regulation, co-regulation, and shared regulation in collaborative learning environments. In *Handbook of Self-Regulation of Learning and Performance* (2nd ed.). Routledge.
- Hernández-Sellés, N., Muñoz-Carril, P.-C., & González-Sanmamed, M. (2019). Computer-supported collaborative learning: An analysis of the relationship between interaction, emotional support and online collaborative tools. *Computers & Education*, 138, 1–12. <https://doi.org/10.1016/j.compedu.2019.04.012>
- Huang, X., & Lajoie, S. P. (2024). A scoping review on effective measurements of emotional responses in teamwork contexts. *Current Psychology*, 43(31), 25661–25682. <https://doi.org/10.1007/s12144-024-06235-7>
- Huang, X., Wu, H., Liu, X., & Lajoie, S. P. (2025). What makes teamwork work? A multimodal case study on emotions and diagnostic expertise in an intelligent tutoring system. In A. I. Cristea, E. Walker, Y. Lu, O. C. Santos, & S. Isotani (Eds.), *Artificial intelligence in education* (Lecture notes in computer sciences Vol. 15881, pp. 44–52). Springer. https://doi.org/10.1007/978-3-031-98462-4_6
- Isöhätälä, 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., & Hadwin, A. F. (2013). New frontiers: Regulating learning in CSCL. *Educational Psychologist*, 48(1), 25–39. <https://doi.org/10.1080/00461520.2012.748006>
- Järvelä, S., & Hadwin, A. (2024). Triggers for self-regulated learning: A conceptual framework for advancing multimodal research about SRL. *Learning and Individual Differences*, 115, Article 102526. <https://doi.org/10.1016/j.lindif.2024.102526>
- Järvelä, S., Volet, S., & Järvenoja, H. (2010). Research on motivation in collaborative learning: Moving beyond the cognitive–situative divide and combining individual and social processes. *Educational Psychologist*, 45(1), 15–27. <https://doi.org/10.1080/00461520903433539>
- Järvelä, S., Kirschner, P. A., Panadero, E., Malmberg, J., Phielix, C., Jaspers, J., Koivuniemi, M., & Järvenoja, H. (2015). Enhancing socially shared regulation in collaborative learning groups: Designing for CSCL regulation tools. *Educational Technology Research and Development*, 63(1), 125–142. <https://doi.org/10.1007/s11423-014-9358-1>
- Järvelä, S., Järvenoja, H., Malmberg, J., Isöhätälä, J., & Sobocinski, M. (2016a). How do types of interaction and phases of self-regulated learning set a stage for collaborative engagement? *Learning and Instruction*, 43, 39–51. <https://doi.org/10.1016/j.learninstruc.2016.01.005>

- Järvelä, S., Kirschner, P. A., Hadwin, A., Järvenoja, H., Malmberg, J., Miller, M., & Laru, J. (2016b). Socially shared regulation of learning in CSDL: Understanding and prompting individual- and group-level shared regulatory activities. *International Journal of Computer-Supported Collaborative Learning*, 11(3), 263–280. <https://doi.org/10.1007/s11412-016-9238-2>
- Järvelä, S., Gašević, D., Seppänen, T., Pechenizkiy, M., & Kirschner, P. A. (2020). Bridging learning sciences, machine learning and affective computing for understanding cognition and affect in collaborative learning. *British Journal of Educational Technology*, 51(6), 2391–2406. <https://doi.org/10.1111/bjet.12917>
- 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., Törmänen, T., Lehtoaho, E., Turunen, M., Suoraniemi, J., & Edwards, J. (2025). Investigating peer influence on collaborative group members' motivation through the lens of socially shared regulation of learning. *British Journal of Educational Psychology*. <https://doi.org/10.1111/bjep.12754>
- Kazemitabar, M., Lajoie, S. P., & Doleck, T. (2019). Examining changes in medical students' emotion regulation in an online PBL session. *Knowledge Management & E-Learning*, 11(2), 129–157.
- Kovanovic, V., Joksimovic, S., Gasevic, D., & Hatala, M. (2014). Automated cognitive presence detection in online discussion transcripts. *CEUR Workshop Proceedings*, 1137.
- Kreibig, S. D. (2010). Autonomic nervous system activity in emotion: A review. *Biological Psychology*, 84(3), 394–421. <https://doi.org/10.1016/j.biopsycho.2010.03.010>
- Kwon, K., Liu, Y.-H., & Johnson, L. P. (2014). Group regulation and social-emotional interactions observed in computer supported collaborative learning: Comparison between good vs. poor collaborators. *Computers & Education*, 78, 185–200. <https://doi.org/10.1016/j.compedu.2014.06.004>
- Lajoie, S. P. (2017). Learning science applications for research in medicine. In Lin, L., & Spector, J. M. (Eds.) *The sciences of learning and instructional design* (pp. 108–118). Routledge.
- Lajoie, S. P., Lee, L., Poitras, E., Bassiri, M., Kazemitabar, M., Cruz-Panesso, I., Hmelo-Silver, C., Wiseman, J., Chan, L. K., & Lu, J. (2015). The role of regulation in medical student learning in small groups: Regulating oneself and others' learning and emotions. *Computers in Human Behavior*, 52, 601–616. <https://doi.org/10.1016/j.chb.2014.11.073>
- Lerchenfeldt, S., Mi, M., & Eng, M. (2019). The utilization of peer feedback during collaborative learning in undergraduate medical education: A systematic review. *BMC Medical Education*, 19(1), 321.
- Lerner, S., Magrane, D., & Friedman, E. (2009). Teaching teamwork in medical education. *Mount Sinai Journal of Medicine, A Journal of Translational and Personalized Medicine*, 76(4), 318–329. <https://doi.org/10.1002/msj.20129>
- Li, S., Zheng, J., Lajoie, S. P., & Wiseman, J. (2021). Examining the relationship between emotion variability, self-regulated learning, and task performance in an intelligent tutoring system. *Educational Technology Research and Development*, 69, 673–692.
- Li, S., Huang, X., Wang, T., Pan, Z., & Lajoie, S. P. (2022a). Examining the interplay between self-regulated learning activities and types of knowledge within a computer-simulated environment. *Journal of Learning Analytics*, 9(3), 152–168.
- Li, S., Zheng, J., & Lajoie, S. P. (2022b). Temporal structures and sequential patterns of self-regulated learning behaviors in problem solving with an intelligent tutoring system. *Educational Technology & Society*, 25(4), 1–14.
- Li, Y., Liu, Y., Nguyen, A., Shi, H., Vuorenmaa, E., Järvelä, S., & Zhao, G. (2024). Interactions for socially shared regulation in collaborative learning: An interdisciplinary multimodal dataset. *ACM Transactions on Interactive Intelligent Systems*, 14(3), 1–34.
- Liu, Y., & Ye, Y. (2025). Exploring how group cooperative learning affect college students' online self-regulated learning—The important role of socially shared regulation, perceived task value, and teacher support. *European Journal of Psychology of Education*, 40(1), 11.
- 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., Haataja, E., Seppänen, T., & Järvelä, S. (2019). Are we together or not? The temporal interplay of monitoring, physiological arousal and physiological synchrony during a collaborative exam. *International Journal of Computer-Supported Collaborative Learning*, 14, 467–490.
- Marlow, S. L., Salas, E., Landon, L. B., & Presnell, B. (2016). Eliciting teamwork with game attributes: A systematic review and research agenda. *Computers in Human Behavior*, 55, 413–423. <https://doi.org/10.1016/j.chb.2015.09.028>
- McHugh, M. L. (2012). Interrater reliability: The kappa statistic. *Biochemia Medica*, 22(3), 276–282.

- Moreno, M., Melo, L. P., Grewal, K., Matin, N., Azher, S., & Harley, J. M. (2024). Analyzing multimodal data to understand medical trainees' regulation strategies and physiological responses in high-fidelity medical simulation scenarios. *Metacognition and Learning*, 19, 1161–1213.
- Moreno, M., Patino-Melo, L., Grewal, K., Pekrun, R., Lajoie, S., Hadwin, A., ... & Harley, J. M. (2025). The role of leadership in medical trainee team-regulation dynamics in crisis resource management simulation education. *European Journal of Psychology of Education*, 40(1), 1–27.
- Näykki, P., Järvelä, S., Kirschner, P. A., & Järvenoja, H. (2014). Socio-emotional conflict in collaborative learning—A process-oriented case study in a higher education context. *International Journal of Educational Research*, 68, 1–14. <https://doi.org/10.1016/j.ijer.2014.07.001>
- Noroozi, O., Pijera-Díaz, H. J., Sobocinski, M., Dindar, M., Järvelä, S., & Kirschner, P. A. (2020). Multimodal data indicators for capturing cognitive, motivational, and emotional learning processes: A systematic literature review. *Education and Information Technologies*, 25, 5499–5547.
- O'Connor, B. P. (1999). Simple and flexible SAS and SPSS programs for analyzing lag-sequential categorical data. *Behavior Research Methods, Instruments, & Computers*, 31(4), 718–726. <https://doi.org/10.3758/BF03200753>
- Olson, G. M., Herbsleb, J. D., & Reuter, H. H. (1994). Characterizing the sequential structure of interactive behaviors through statistical and grammatical techniques. *Human-Computer Interaction*, 9(3–4), 427–472. <https://doi.org/10.1080/07370024.1994.9667212>
- Open AI. (2023). *Whisper transcription* (7.9.1) [Computer software]. Retrived November 21, 2023, from <https://openai.com/research/whisper>
- Pacak, K., Eisenhofer, G., Ahlman, H., Bornstein, S. R., Gimenez-Roqueplo, A.-P., Grossman, A. B., Kimura, N., Mannelli, M., McNicol, A. M., & Tischler, A. S. (2007). Pheochromocytoma: Recommendations for clinical practice from the First International Symposium. *Nature Clinical Practice Endocrinology & Metabolism*, 3(2), 92–102. <https://doi.org/10.1038/ncpendmet0396>
- Perry, N. E., & Winne, P. H. (2012). *Tracing students' regulation of learning in complex collaborative tasks*. Routledge.
- Pijera-Díaz, H. J., Drachsler, H., Järvelä, S., & Kirschner, P. A. (2016). Investigating collaborative learning success with physiological coupling indices based on electrodermal activity. *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*, 64–73. <https://doi.org/10.1145/28838351.2883897>
- Pijera-Díaz, H. J., Drachsler, H., Kirschner, Pa., & Järvelä, S. (2018). Profiling sympathetic arousal in a physics course: How active are students? *Journal of Computer Assisted Learning*, 34(4), 397–408. <https://doi.org/10.1111/jcal.12271>
- Pijera-Díaz, H. J., Drachsler, H., Järvelä, S., & Kirschner, P. A. (2019). Sympathetic arousal commonalities and arousal contagion during collaborative learning: How attuned are triad members? *Computers in Human Behavior*, 92, 188–197. <https://doi.org/10.1016/j.chb.2018.11.008>
- Salas, E., Sims, D. E., & Burke, C. S. (2005). Is there a “Big Five” in teamwork? *Small Group Research*, 36(5), 555–599. <https://doi.org/10.1177/1046496405277134>
- Schunk, D. H., & Zimmerman, B. J. (2007). Influencing children's self-efficacy and self-regulation of reading and writing through modeling. *Reading & Writing Quarterly*, 23(1), 7–25. <https://doi.org/10.1080/10573560600837578>
- Sharma, K., Nguyen, A., & Hong, Y. (2024). Self-regulation and shared regulation in collaborative learning in adaptive digital learning environments: A systematic review of empirical studies. *British Journal of Educational Technology*, 55(4), 1398–1436.
- Silvia, P. J., Beaty, R. E., Nusbaum, E. C., Eddington, K. M., & Kwapil, T. R. (2014). Creative motivation: Creative achievement predicts cardiac autonomic markers of effort during divergent thinking. *Biological Psychology*, 102, 30–37.
- 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(2), 99–127. <https://doi.org/10.1007/s11409-020-09224-w>
- Sobocinski, M., Malmberg, J., & Järvelä, S. (2022). Exploring adaptation in socially-shared regulation of learning using video and heart rate data. *Technology, Knowledge and Learning*, 27(2), 385–404.
- Törmänen, T., Järvenoja, H., & Mänty, K. (2021). All for one and one for all – How are students' affective states and group-level emotion regulation interconnected in collaborative learning? *International Journal of Educational Research*, 109, Article 101861. <https://doi.org/10.1016/j.ijer.2021.101861>
- Törmänen, T., Järvenoja, H., Saqr, M., Malmberg, J., & Järvelä, S. (2022). A person-centered approach to study students' socio-emotional interaction profiles and regulation of collaborative learning. *Frontiers in Education*, 7, Article 866612. <https://doi.org/10.3389/educ.2022.866612>

- Winne, P. H. (2015). What is the state of the art in self-, co- and socially shared regulation in CSCL? *Computers in Human Behavior*, 52, 628–631. <https://doi.org/10.1016/j.chb.2015.05.007>
- 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). Erlbaum.
- Winne, P. H., Nesbit, J. C., Kumar, V., Hadwin, A. F., Lajoie, S. P., Azevedo, R., & Perry, N. E. (2006). Supporting self-regulated learning with study software: The learning kit project. *Technology, Instruction, Cognition and Learning*, 3, 105–113.
- Wright, M. C., Phillips-bute, B. G., Petrusa, E. R., Griffin, K. L., Hobbs, G. W., & Taekman, J. M. (2009). Assessing teamwork in medical education and practice: Relating behavioural teamwork ratings and clinical performance. *Medical Teacher*, 31(1), 30–38. <https://doi.org/10.1080/01421590802070853>
- Xu, W., & Lou, Y. F. (2024). Changes in the socially shared regulation, academic emotions, and product performance in venue-based collaborative learning. *Active Learning in Higher Education*, 25(3), 517–535.
- Zhao, K., Wulder, M. A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X., & Brown, M. (2019). Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A bayesian ensemble algorithm. *Remote Sensing of Environment*, 232, Article 111181. <https://doi.org/10.1016/j.rse.2019.04.034>
- Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory into Practice*, 41(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2
- Zimmerman, B. J., & Schunk, D. H. (2011). *Self-regulated learning and performance: An introduction and an overview*. Routledge.

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Current themes of research

The current themes of research focus on learners' socially shared regulation in problem-solving teamwork tasks, including interactions of metacognition, cognition, motivation and emotions in collaborative learning.

Most relevant publications

- Huang, X., & Lajoie, S. P. (2024). A scoping review on effective measurements of emotional responses in teamwork contexts. *Current Psychology*, 43(31), 25661–25682. <https://doi.org/10.1007/s12144-024-06235-7>
- Järvelä, S., & Hadwin, A. (2024). Triggers for self-regulated learning: A conceptual framework for advancing multimodal research about SRL. *Learning and Individual Differences*, 115, 102526. <https://doi.org/10.1016/j.lindif.2024.102526>
- Huang, X., & Lajoie, S. P. (2023). Social emotional interaction in collaborative learning: why it matters and how can we measure it?. *Social Sciences & Humanities Open*, 7(1), 100447.

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