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Abstract

Emotional regulation in learning has been recognised as a critical factor for collaborative learning success. However, the "unobservable" processes of emotion and motivation at the core of learning regulation have challenged the methodological progress to examine and support learners' regulation. Artificial intelligence (AI) and learning analytics have recently brought novel opportunities for investigating the learning processes. This multidisciplinary study proposes a novel fine-grained approach to provide empirical evidence on the application of these advanced technologies in assessing emotional regulation in synchronous computer-support collaborative learning (CSCL). The study involved eighteen university students (N=18) working collaboratively in groups of three. The process mining analysis was adopted to explore the patterns of emotional regulation in synchronous CSCL, while AI facial expression recognition was used for examining learners' associated emotions and emotional synchrony in regulatory activities. Our findings establish a foundation for further design of human-centred AI-enhanced support for collaborative learning regulation.

Keywords: emotional regulation, artificial intelligence, synchronous computer-supported collaborative learning (CSCL), learning analytics information systems (LAIS)

Introduction

The recent rapid growth of information systems (IS) in education has opened novel opportunities for learning and teaching (Martínez-Cerdá et al., 2020). The role of IS in education is ever highlighted through the challenges caused by the COVID-19 pandemic, in which the use of educational IS is critical to maintaining continuous learning and teaching in social distancing conditions. Notably, educational IS does not only offer the means for distance education but also provides novel approaches to investigate the learning and teaching processes (Tukshumskaya, 2020). For example, the development and implementation of learning analytics information systems (LAIS) have exploited learners' digital traces to reveal new insights into their learning behaviour (Baker et al., 2021; Nguyen, Tuunanen, & Gardner et al., 2021). While learning theories have informed the design of educational IS, the development of educational

IS has promoted methodological progress, hence enabling theory advancement in learning sciences (Reimann, 2019). Especially, the use of advanced technologies such as artificial intelligence (AI) has allowed for examining complex and dynamic learning processes such as self-regulated learning and collaborative learning (Di Mitri et al., 2017).

Emotional regulation has been recognised as an essential skill for collaborative learning success. Collaborative learning involves not only learners' knowledge and skills but also their emotions and interpretations of other group members' emotions while working towards a common goal. Accordingly, previous studies have indicated that socio-emotional interaction is an essential element of collaborative learning but can lead to challenges that inhibit group functioning and emotional regulation (Hadwin et al., 2018; Malmberg et al., 2019). Understanding and supporting learners' emotional regulation would improve collaborative learning. However, several methodological challenges have been documented in measuring and supporting learning regulation (Azevedo & Gašević, 2019; Järvelä et al., 2020; Winne, 2014). For instance, the cognitive and emotional processes at the core of learning regulation are "unobservable" by humans. Traditional methods such as surveys and interviews could not avoid biases in measuring and aggregating data for emotional regulation. These methods could mostly capture the "perceived" emotion rather than the actual emotions of the learners. Furthermore, the dynamic and cyclical natures of the regulatory process make it difficult to fully capture using traditional methods (Järvelä et al., 2019). It is even more challenging to examine emotional regulation in collaborative learning due to the dynamics of interactions among the learners (Nguyen et al., 2022).

Fortunately, the advances in educational technology have shed new light on understanding and measuring learning regulation. The availability of new data channels and sophisticated analysis techniques with advanced technologies have offered new opportunities to explore learning regulation in various contexts (Dindar et al., 2020; Järvelä & Bannert, 2021). There have been several recent calls for multidisciplinary efforts in bridging learning sciences, IS, AI machine learning, and other related domains for utilising advanced technologies to better understand learning (Järvelä et al., 2020) as well as to design effective learning support (Nguyen, Tuunanen, & Gardner et al., 2021). In this paper, we respond to these calls by considering how AI technologies could be utilised to investigate learning regulation in collaborative learning.

While several attempts have been made to examine learning regulation in asynchronous computer-supported collaborative learning (CSCL), much less is known about learning regulation in synchronous CSCL. Prior to the COVID-19 pandemic, the research on regulation in CSCL contexts mainly involved asynchronous learning settings, such as those on learning management systems (LMS) (Cicchinelli et al., 2018) or Massive Open Online Courses (MOOCs) (Chaker & Impedovo, 2021). The need for synchronous CSCL on platforms such as Microsoft Teams and Zoom has dramatically increased alongside hybrid and online learning through the pandemic. Despite the importance of learning regulation, especially in the challenging context of the COVID-19 pandemic, the literature review conducted revealed a paucity of evidence on learning regulation in synchronous CSCL. Furthermore, although the need for emotional regulation has been highlighted through the pandemic (Zhao et al., 2021), few studies have closely examined emotional regulation in synchronous CSCL. Accordingly, this study seeks to reveal new insights into learning regulation in a synchronous CSCL context. In particular, the following research questions have been formulated to guide this study:

1) How does emotional regulation occur in synchronous CSCL?

2) How could AI facial expression recognition be utilised to inform the emotional process related to learning regulation in synchronous CSCL?

The following section reviews the theoretical grounding of learning regulation and methodological progress towards AI applications in learning regulation research. Then, we describe the data collection and analysis methods applied in this study. Thereafter, we demonstrate our results and findings together with the comparison with previous studies. Finally, we discuss our study's main contributions and potential implications, and we conclude by discussing its limitations and future research directions.

Theoretical Background

Regulatory Challenges and Emotional Regulation in Collaborative Learning

In the new global economy, collaboration has become a central issue, and yet, despite its benefits, successful ones are rarely achieved. Collaboration is a process of working toward a shared goal and strategies, yet it is coordinated by a group of different cognition, metacognition, motivation, and emotional perspectives. Besides external challenges, such as task difficulty or lack of support, the collaboration context requires a greater level of commitment and concentration that typically results in a higher level of social-emotional challenges (i.e. motivation conflicts, different working styles, interpersonal dynamics) (Van den Bossche et al., 2006). Simply putting learners into a group for collaborative activities does not automatically guarantee learning success. Instead, to succeed in constructing new knowledge and understanding, learners need to overcome cognitive challenges in understanding and negotiating others' thinking processes, motivation, and emotional challenges in aligning group members' goals and expectations (Bakhtiar & Hadwin, 2020).

Previous research has established that at the individual level, most learners lack the ability and motivation to regulate their learning. When confronted with complex collaboration tasks with amplified challenges, learners will be challenged to double their cognitive load in order to solve the present problem while developing the necessary regulatory skills, resulting in a deleterious effect on both processes (Kirschner & Van Merriënboer, 2013). For that reason, recent developments in CSCL have heightened the need for identifying mediators and conditions for effective regulatory processes in collaboration, leading to newly generated evidence about the interconnection between emotion regulation and regulated learning as a whole.

Emotional regulation in collaborative learning involves the capacity to manage one's emotions and to understand others' emotions and feelings (Järvenoja et al., 2018). By conceptualising regulation as a social, interactive, dynamic, temporal, and evolving process, contemporary Regulation Learning Theory has placed motivation and emotion, which were largely ignored in collaborative learning literature, at the forefront of this process. Emotion is socially constructed but personally enacted (Schutz et al., 2006). Social learning situations of collaboration can induce positive and negative emotions that can advance or hinder interaction and engagement within a group. Recent research has revealed that emotions can trigger a variety of dispositions that change the interpretation of the subsequent event (Lerner et al., 2015), such as learners' beliefs and attitudes towards the tasks, how they feel about the social situation, how they approach the collaboration, and how they self-evaluate their strategies and goal. Without awareness and active control of emotion and motivation, especially in the face of socioemotional challenges and unfavourable external conditions (e.g. family emergencies), this will result in withdrawal of interest, misaligned task goals and strategies, social distancing toward the group and the task (Avry et al., 2020), hindering engagement and participation. While perceived as undesirable, emerging negative emotional interactions invite the groups to regulate the situation and the affective states. Therefore, emotion regulation is critical in effective collaboration and SSRL as it can adjust the group's emotions and motivation and prompt a shift toward empathetic attitudes that foster group understanding, reconsidering, and synchronising.

The role and importance of emotion regulation in SSRL and collaboration learning are evident. So far, however, with the dominant application of traditional self-report research methodology (Paris & Turner, 2012), the mechanism of how motivation and emotion regulation is triggered and influence SSRL during collaboration, especially pertaining to the different proximal level of (S)SRL and how it intertwined with other learning processes, are not fully understood (Järvenoja et al., 2018). The past two decades have witnessed an explosion of CSCL technology to support productive social interaction and the construction of knowledge. While most of them predominantly support collaborative communication and not the socially shared regulatory process, CSCL and advanced learning analytics show their potential in providing the field with a novel multimodal channel of data that is objective and process-oriented such as trace data or physiological data (Järvelä et al., 2019; Pijeira-Díaz, 2019). These can shed light on emotion regulation's temporal, sequential, and situated nature in an authentic learning context.

Methodological Progress and Challenges in Studying Learning Regulation

The complexity of understanding SRL has brought about several methods to capture and learn the dynamics of SRL, CoRL, and SSRL to inform learning practices and outcomes. Hadwin et al. (2018) have consistently maintained that all three types of regulation learning emerge in the context of truly collaborative learning. Numerous empirical findings have validated this sentiment (e.g., Ucan & Webb, 2015; Zheng & Yu, 2016). However, regardless of the SRL models, learning regulation processes are difficult to measure (Winne, 2018), which brings the need to transition from traditional methods to multimethodological approaches to capture both objective and subjective traces of the regulatory processes (Järvelä et al., 2019).

The first challenge noted by a systematic review conducted by Järvelä et al. (2019), is that regulation does not occur linearly; instead, it involves a temporal and cyclical adaptation that is challenging to capture. Learners are constantly utilising their metacognition to strategically adapt their learning if needed, and these cycles of learning adaptation may vary across each iteration (Zimmerman, 2013). Second is the challenge of identifying how the three models of SRL, as highlighted by Hadwin et al. (2018), collectively contribute to successful learning in the collaborative or CSCL context. While Järvelä et al. (2015) and Järvenoja et al. (2015) have identified the critical processes and contributions of SSRL to the success in collaborative learning, most current research has predominantly focused on the SSRL processes themselves rather than understanding how the three primary forms of regulation, i.e., SRL, CoRL, and SSRL collectively contribute to learning success. The third challenge is the need to holistically comprehend and capture each learner's various intertwined elements (e.g., emotion, motivation, cognition). The psychological processes at the heart of regulation are intangible, which adds to the challenge of understanding the regulatory process, reducing the ability to support and influence learners towards a more productive and effective SSRL (Järvelä et al., 2019).

The challenges have since offset an evolution of data collection methods in the SRL field. Considering the dynamic nature of regulation, retrospective approaches consisting of subjective measures such as self-reported data (e.g., interviews and surveys) are deemed insufficient to capture the exact moments when those regulatory actions occur and how these actions influence each other. This led to a rising emphasis on trace data or real-time measurements as individuals are engaged in learning tasks (Azevedo et al., 2019). Multimodal data, such as log files of time-stamped descriptions of observable interactions between learners and content, eye-tracking, think-aloud protocols, screen recording of human-machine and human-human interactions, and physiological sensors, though currently is still somewhat implemented sparingly in the SRL field, are deemed useful in providing objective insights into the patterns and changes in the regulatory processes with specific timeframes (Azevedo & Gašević, 2019; Dindar et al., 2020).

Furthermore, learning regulation may be imposed on learners as they do not always realise or are unwilling to grasp the opportunities for regulation in collaboration. This saw an increase in the implementation of technological tools, such as CSCL, to prompt and reinforce SRL, CoRL, and SSRL. While these tools have been found effective in supporting individual SRL and monitoring metacognition, less effort has been made to support SSRL in groups (Schnaubert & Bodemer, 2017). Aside from regulatory prompts to promote group awareness, these tools can be utilised to trace individuals' engagement, cognitive, emotional, and motivational states, and visualisations of individuals' regulatory plans and perceived challenges in tasks and identify how shared regulation is substantiated when prompted and resulting evaluations (Järvelä et al., 2019; Järvenoja et al., 2015).

Nevertheless, gathering in-situ SSRL data on challenges faced by learners in authentic learning tasks is essential as this provides the opportunity to explore the unique makeup of learners and their interactions when challenges emerge, as well as what challenges faced in different social, technological, and contextual features and trace the regulation as it evolves within a given situation. For instance, a study by Järvenoja et al. (2018) on student teachers' collaborations across different mathematical tasks in CSCL revealed an emergence of a wide range of micro-level challenges (i.e., cognition, emotion, motivation, social, and contextually oriented challenges. The challenging episodes learners face when navigating through the tasks can be considered triggers in activating regulatory activities, and the multidimensional aspects of regulatory activities also differ over the course of collaborations (Järvelä et al., 2015; Nasir et al., 2021). The situative perspective allows for rich multilayer data considerations such as objective data (e.g., physiological responses and eye-tracking), triangulated with subjective data (e.g., learners' conceptions and intent) to help understand traces of regulatory behaviors and "processes as temporally unfolding events that are contextualised in situ" (Järvelä et al., 2019, p. 434).

While multimodal approaches with the application of emerging technologies would propel the SRL field towards a more holistic interference of the learning process (Harley et al., 2015), this method is still relatively novel in the SRL field. More work needs to be done to increase the reliability and validity of the methodology. Currently, multimodal data are narrow in scope and are often accompanied by different sampling rates (Acuña, Lopez Aymes & Acuña-Castillo, 2018). Next, there are still difficulties aligning the different types of multimodal data for analysis. More research corroboration is also needed to pinpoint the significance of these modalities in revealing specific events and measures of the learning and collaboration processes (Järvelä et al., 2019).

In addition, there is still a lack of objective, quantifiable measures for comparisons and tracking of learning regulations in SSRL and the external generalised context. Nevertheless, the conventional statistical and data mining techniques used to detect, measure, and infer the complex and messy aspects of the learning regulation process fragmentised the findings. Leveraging artificial intelligence technology would also help widen the multimodal data channels, increase the understanding of the complex processes by tracing and detecting more regulatory markers to augment advanced learning technologies to provide a more holistic, real-time, intelligent, and personalised scaffolding and feedback according to each individual regulatory needs (Azevedo & Gašević, 2019; Järvelä et al., 2019; Srivastava et al., 2022).

Artificial Intelligence (AI) Opportunities for Learning Regulation Research

As aforementioned, with emotion, motivation, and cognitive processes being at the core of learning regulation, emerging technologies would play a vital role in capturing the intricacy of these regulatory processes (Azevedo & Gašević, 2019; Järvelä et al., 2019). While emotions are traditionally assumed to be either an indication of an individual's internal states or an outlet for displaying individuals' orientation to what is happening to others, emotions are also attuned to interpersonal responses (Rogat & Adams-Wiggins, 2015). Emotions have deep influences on learners' cognitive processes, where positive emotions would increase learners' attention, reasoning, and problem-solving, leading to motivating learning behaviors (Tyng et al., 2017).

In a collaborative setting, the emotional expression of a group member is shaped by the atmosphere of the group, either harmonising or deviating group responses. For example, individuals who received a hostile reaction, such as an unhappy facial expression, would feel rejected and, in turn, contribute less collaboratively (Heerdink et al., 2013). The social contagion of emotions amongst interacting individuals in a group effectively functions as a regulator and facilitator in the transference of a particular learning experience (Lakin & Chartrand, 2003).

While the overall learning experiences are evident after an event, it is often difficult to capture and measure the fluidity of the short-term affective states of individuals. In the collaborative learning context, different states of emotions spread and are mimicked amongst all group members through cycles of interactions (Rogat & Adams-Wiggins, 2015). Emotional mimicry, for instance, has been validated by studies as a marker of initial affiliative bond and empathy amongst individuals. Furthermore, the transient states of emotion in accordance with the learning tasks' progress and continual relations with others influence coordination and group cohesion. Understanding and capturing these temporal cycles of emotions and emotional contagion in a fine-grained manner would better help identify pain points in SSRL and timely prompts and cues to help regroup members and maintain the quality of the learning experience (Dindar et al., 2020).

A promising technique for identifying temporal and cyclical emotions in the collaborative learning context would be the implementation of a time-stamped video-based facial expression recognition method. The method, comprising of time-stamped frames, is useful in providing the fine-grained level of details (Dindar et al., 2020), for instance, the exact moment of changes in facial expressions, matching to the specific tasks that learners were working on. Furthermore, the analysis of the audio captured would provide a richer context for understanding the regulatory dynamics and social atmosphere of the group at a given point in time.

As mentioned earlier, multimodal approaches and analyses would enhance a deeper understanding of learners' learning regulation. However, current techniques to collect multimodal data are often narrow in scope (Järvelä et al., 2019; Acuña et al., 2018). Furthermore, the lack of integration among research systems and sensors with manual coding of facial expressions, speech, and gestures poses data triangulation and validity challenges. Given that, there are now emerging technologies powered by Artificial Intelligence (AI) in assisting in multimodal data collections, with deep learning analysis and, in turn, real-time improved personalised and predictive abilities based on machine learning algorithms (Graham et al., 2020).

From a methodological perspective, AI technologies have the ability not only to increase the accuracy of the frame-by-frame analysis of emotions but, when integrated with physiological sensors (Zhang et al., 2020) or triangulated with audio data, would increase the depth of analysis. This results in learned and customised responses based on real-time identification of regulation and inserting of prompts to help regulate individuals' learning needs more effectively. While this is still ongoing progress in the educational sphere, AI solutions have been highly utilised in other sectors. For example, the healthcare sectors harness AI's role to automatically recognise emotions based on facial expressions and employ machine learning techniques to predict and detect cognitive decline in the elderly. Aside from its ability to study and mimic human emotions and cognitive functions, AI technologies are also capable of supporting the integration and alignment of different types of multimodal data, for instance, psychological, biological, and social factors, which in the medical context, aids clinical decision makings: diagnosis, differentiation between various types of cognitive dissonances (Graham et al., 2020), and prescriptions of appropriate interventions (Zhang et al., 2020).

Methods

Data Collection

Participants and Contexts

This study involved eighteen university students (N=18), aged twenty years old, collaboratively working in groups of three. The research was carried out in an Academic English course, and their participation was entirely voluntary with the provision of written informed consent. Students also received monetary compensation after they participated in the study. During the whole semester, students had many opportunities to join collaborative writing sessions to practice their academic writing skills. However, this study merely focuses on data collection of typical collaborative writing activity, in which students were required to form groups of three to discuss and complete a writing task. Due to the Covid-19 pandemic, all the lessons were conducted in virtual classrooms, so all the groups were instructed to join breakout rooms and record themselves. In total, three hours of video data were collected for six groups with an average of 30-minute each.

Procedure

Before partaking in the collaborative writing activity, students were required to sit in a quiet environment to minimise background noises and perform quality checks (i.e., headphones, internet connection, camera) to quickly resolve technical problems and minimise unexpected interference. Students were given a choice to share their computer screens, but all participants' cameras needed to be turned on during the collaborative session. This was to help capture their facial expressions, postures, and hand gestures. As for the learning tasks, the participants were given a topic to discuss in groups with a time constraint of 30 minutes. The participants were required to form an outline, followed by a written paragraph in English about the topic, e.g., the causes of air. The lecturer explained the structure of the tasks at the beginning of the session, and participants were not given any support or feedback during the entirety of the collaborative session. The outcome of the task was a 200-word paragraph at an advanced (C1) level and was assessed based on the official marking rubrics of the Common European Framework of Reference for Languages (CEFR).

Data Analysis

Video recordings of students' collaborative writing sessions were analysed through video coding and AI facial expression recognition (FER) analysis. A process mining approach was adopted for revealing emotional regulation patterns in synchronous CSCL while quantitative statistical analysis of aligned video coding and AI FER outputs informed the learners' emotions related to different regulatory activities.

Video Qualitative Analysis

A coding scheme is adopted from previous studies (Järvenoja et al., 2019; Malmberg et al., 2017) to determine how participants showed their initiative in taking the lead and following behaviours as responses to verbal and non-verbal interactions in a collaborative task. Nevertheless, rather than analysing the video by assessing it in 30-second segments, this study attempts to apply a more granular and sophisticated approach. The 30-second segment video analysis has been criticised as insufficient for the machine learning approach (Nguyen et al., 2022). In this coding scheme, a code is assigned to a talking turn of a group member during collaboration. First, the main focus of each group's interaction is coded: cognitive interactions, task execution, socio-emotional interactions through verbal, bodily, emotionally charged indicators, and other non-task-related activities. Second, regarding the types of challenges, the code is used when participants clearly showed cognitive struggles in dealing with the task, emotional and motivational difficulties controlling their negative emotions, and social context and interaction challenges in the working environment, communication, and teamwork. Third, emotional regulation strategies are coded when participants indicate their encouragement, social reinforcement by securing a positive atmosphere, task structuring to reorient task behaviour of unfocused members, and increasing awareness to help group members regulate negative emotions.

The video recordings and transcripts were simultaneously used to code students' behaviours and how they interacted with each other during the collaborative task. Two independent researchers participating in the coding phase, after being instructed about the coding scheme, piloted a video recording to measure the inter-rater consistency. Cohen's kappa coefficient recorded an agreement of 0.71 (Interaction); 0.84 (Challenge); and 0.83 (Emotion Regulation Strategies), suggesting high reliability of the coded data. Then two researchers were then assigned to code the remaining video recordings separately, and researcher-researcher corroboration was also conducted to discuss problems arising during the coding process. Table 1 demonstrates the coding scheme for qualitative video analysis.

Categories	**Description**	**Examples**
Regulatory Interactions		
Cognitive interaction	Interaction focuses on the learning-related higher mental process toward metacognitive level (monitoring and controlling) when dialogues focus on: - Establishing task demands - Activating prior knowledge - Evaluating and selecting resources and strategies - Checking and evaluating task progression, solution, and overall performance.	*Our topic is to find out the reason for air pollution, right? So, I found two ideas which are from transportation. Or is it transition?* *S1: We need to research first!* *S2: Why should we for a B1 B2 English level?* *S1: In the document, it said the writing will be assessed based on the C1 level, right?*
Socio-emotional interaction	Interaction focuses on strong expressions of socio-emotion with clear negative/positive affect nature (e.g., showing gratitude, approving, joking, disputing, criticising, being ironic). This could be task-related or non-task interaction. Expression included verbal (content, tones) and/or non-verbal indicators (e.g., smiling, laughing, frowning, sighing, moaning, facepalm).	*So annoying! I only got a B for Political Economy.* *S1: It kept flickering, so annoying!* *S2: It's too loud in my place, right? [expressing annoyance]* *S1: No, I couldn't hear anything.*
Task execution interaction	Interaction that primary focus on carrying out task requirement, and completing the task: - Writing out the task	*[Tying and read aloud] ... CO2 and SO2...*

	- Read task instruction - Sharing the file, link, etc. - No clear and/or strong affect is indicated.	*[Saying out loud] I am sending the docs link now.*
Other interaction	Interaction that is not related to the task topic or objective. E.g., talking about: - Out-of-school or school-related activities. - Current learning situation or environment without clear indicators of significant emotion	*S1: I can hear what Hang said echo all till here in Zoom.* *S2: Of course, being in the same room will have some differences.* *I usually got a B for non-main subjects. Like, [I] couldn't put too much effort into it.*
Regulatory Challenges		
Cognitive challenge	Coded when group member(s) indicated difficulties related to higher learning mental processes such as memory processing, understanding task, finding solutions, ability to solve the task by choosing answers, strategies, etc.	*But those things don't have a clear effect. It wouldn't make a strong point. [Stuck and doesn't know what to use instead]*
Emotional and motivational challenge	Coded when group member shows clear indicators of negative emotion, their inability to control them that is hindering the task progression. This included annoyance, frustration, anxiety, boredom, lack of interest, self-confidence, motivation, etc.	*I am scared I am going to make a grammar mistake. [Hesitate to continue the task]* *We should write now or else we won't make it in time.*
Social context and other interaction challenges	Coded when group member experiences other types of difficulties that hinder the task progression. This includes environmental context such as resources-related issues (technology, time, tools) or social context such as conflict of working style, and communication.	*Shall I turn off the shared screen, it's blocking my vision.*
Emotion Regulation Strategies		
Encouragement	Coded when group members provide emotional support to others or the groups by praising or supporting each other.	*Don't worry. This is like a 7.0 equal grade!* *Wow, that is good! Keep going.*
Social Reinforcement	Coded when a group member tries to regulate others' negative emotions and the social atmosphere by highlighting and reassuring the positive aspect of their situation.	*[Members were wondering about the requirement of the task]* *S1: 230 words is a little bit longer, but it is acceptable. It wouldn't cost the grade.*
Task Structuring	Coded when a group member tries to draw the focus to task-related	*[S1 and S2 were negotiating on which term to use and building up hostility]*

	behaviours. This could be to avoid off-task behaviour that causes frustration to other members or to diffuse a potentially tense situation.	*S3: Okay, so how about we just talk in general and then add another criterion here?*
Increasing Awareness	Coded when group members attempt to get others to become more aware of their negative emotions or affect states, thereby facilitating the regulation of these feelings.	*S1: I think you are overthinking, and you don't have to worry to that extent.* *S2: Really?* *S1: Yes, if I was you, I think I would feel like I am trying to think about the effect of that source…*

Table 1. Coding scheme for qualitative video analysis

Process Mining for Emotional Regulation Patterns in Synchronous CSCL

In order to identify and describe the patterns of emotional regulation in synchronous CSCL, we conducted a process-mining analysis with the qualitatively coded regulatory activities. The process-mining analysis was conducted applying the Fuzzy Miner approach (Günther & van der Aalst, 2007) and using Fluxicon's Disco analysis software (https://fluxicon.com/disco/), a process mining software widely used in prior studies to investigate the process of learning events (Dindar et al., 2022; Järvenoja et al., 2019)

AI Facial Expression Recognition for Detecting Learners' Emotions

In spite of the long-established correlation between emotion and learning, a systematic understanding of how student affective/emotional regulation unfolds, and influences learning has remained elusive due to the invisible nature of these cognitive processes (Järvelä et al., 2019). In a classroom setting, especially one-to-one, human teachers are often capable of recognising students' affective states. However, to effectively and efficiently track and analyse the affective states of every student in each group at a more granular level requires large amounts of data and extensive processing power that automatic detection is more capable of handling.

Automatic Facial Expression Recognition (FER) has been a long-researched aspect with an increasing application in the learning and teaching environment to recognise and track students' behaviour. These deep learning algorithms are not only able to detect human emotion directly from video recordings, but also classify the emotion valence on a continuous scale, providing us with the capacity to better understand and analyse students' emotional changes across the recursive cognitive sequence and facet of self-regulation (Hadwin et al., 2005).

Considering the context of our study; a collaborative online learning environment with a small dataset scope, img2pose was selected as our module for facial localisation as it has already been trained on the Wider Face dataset, achieving a reliable performance of 3.9 mean square error (Zhu et al., 2016). For the emotion detection module, Residual Masking Network, a well-established competing method in FER with an accuracy rate of 73.28% on the FER2013 dataset (Khaireddin et al., 2021) was chosen. The discrete emotions were classified into seven categories (anger, disgust, fear, happiness, neutral, sadness, and surprise).

Quantitative Statistical Analysis for Regulation Activities and Emotions Co-Occurrences

Every second of the video is aligned with both facial expression recognition detection results and detailed qualitative coding of regulatory activities. While previous studies have often used 30-second segments of qualitative video coding (e.g., Järvenoja et al., 2019), recent research has suggested that a more granular approach should be adopted for AI methods (Nguyen et al., 2022). As a result, this study is one of the early attempts to examine learning regulation at a micro-level with high graininess.

Python programming language and Jupyter environment were used for data wrangling and alignment, whereas Tableau was utilised to visualise emotions' probability distribution among different regulatory activities. Kruskal-Wallis H Test was conducted to confirm the statistically significant difference in the distribution. Moreover, emotions from different learners in each group were aligned for co-occurrences analysis regarding emotional synchrony. First, a threshold of 0.5 ($p > 0.5$) was employed to determine the emotion of each learner in a group. Emotional synchrony was then recognised whenever two or more group members shared the same emotion. Lastly, a Chi-square test was conducted to inspect the relationship between emotional synchrony and regulatory activities in collaborative learning.

Results and Findings

1) How Does Emotional Regulation Occur in Synchronous CSCL?

An initial objective of the project was to identify the patterns of emotional regulation in synchronous online collaborative learning. Figure 1 shows our process mining results for emotional regulation in synchronous CSCL. The process map reported the most dominant pathways of emotional regulatory activities with absolute frequencies. Although several social interactions ($f_{CognitiveInteraction} = 1277$, $f_{TaskExecutionInteraction} = 255$,

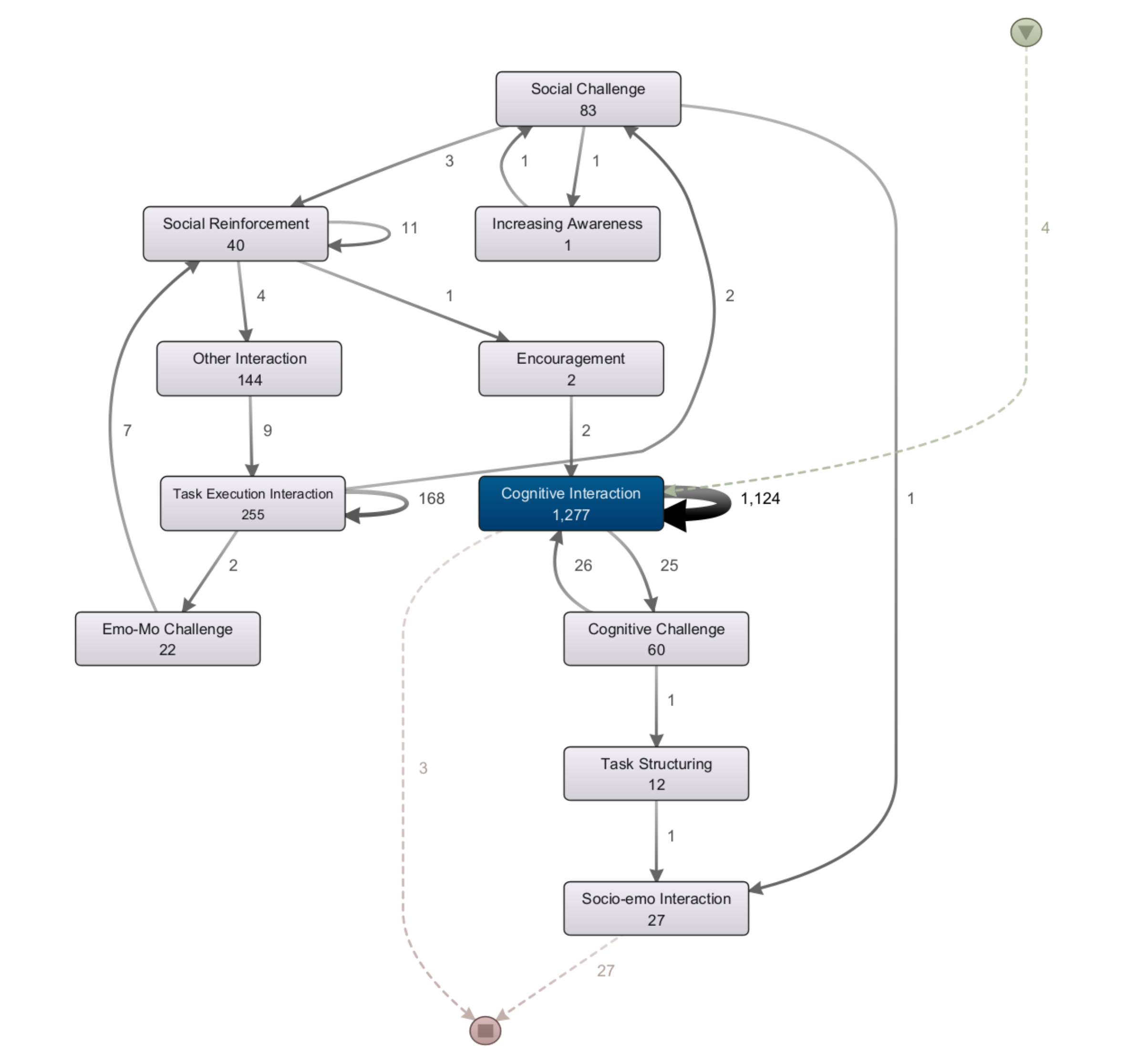

Figure 1. Emotional regulation patterns in synchronous CSCL

$f_{\text{Socio-emoInteraction}} = 27$, $f_{\text{OtherInteraction}} = 144$) and regulatory challenges ($f_{\text{CognitiveChallenge}} = 60$, $f_{\text{SocialChallenge}} = 83$, $f_{\text{Emo-MoChallenge}} = 22$), only a few emotional regulation strategies have been adopted ($f_{\text{Encouragement}} = 2$, $f_{\text{SocialReinforcement}} = 40$, $f_{\text{IncreasingAwareness}} = 40$). This finding is consistent with early studies, which suggested that most of the social interactions for regulation do not actually activate regulation in collaborative learning (Nguyen et al., 2022; Sobocinski et al., 2017). This highlighted the need for providing support to promote regulation in collaborative learning, hence enhancing learning.

As mentioned in the literature review, several reports have shown that learning regulation is essential for the success of both individuals and groups (Dindar et al., 2020; Hadwin et al., 2018). Recent studies have explored the patterns of learning regulation in face-to-face collaboration (Järvenoja et al., 2019) and asynchronous online collaborative learning (Iiskala et al., 2015). Very little was found in the literature on the question of whether similar patterns of learning regulation would occur in a synchronous CSCL context. The results of this study confirm a similar emotional regulation in synchronous CSCL. Furthermore, our process map informs which emotional regulation strategies have been adopted by the learners in response to different types of regulatory challenges. For instance, social reinforcement ($f=3$) and increasing awareness ($f=1$) were used for addressing social challenges, while task structuring ($f=1$) was adopted for coping with cognitive challenges. A note of caution is due here since the occurrence rate of regulation is quite low which, nevertheless, is in accordance with previous studies.

2) How Could AI Facial Expression Recognition Be Utilised to Inform the Emotional Process Related to Learning Regulation in Synchronous CSCL?

The second question in this research was to determine the possibility of applying AI techniques to inform the emotional process related to learning regulation in synchronous CSCL. Prior studies have noted the importance of aligning learning theories and technological aspects of advanced technologies to maximise their impacts on learning and teaching (Järvelä et al., 2020; Nguyen, Järvelä , & Wang et al., 2021). In line with this research trajectory, this study attempted to contribute to the methodological progress in learning regulation research with its demonstrated granular research method. Figure 2 shows the distribution of emotion probabilities among different regulatory activities in synchronous CSCL.

	Activity										
Emotion	Social Challenge	Cognitive Challenge	Emo-Mo Challenge	Cognitive Interaction	Socio-emo Interaction	Task Execution ..	Other Interaction	Encourag..	Increasing Awareness	Social Rein forcement	Task Structuring
Anger	7,95%	4,17%	5,11%	5,10%	8,89%	4,12%	4,58%	2,55%	5,91%	4,23%	8,21%
Disgust	4,97%	1,19%	5,01%	4,12%	5,37%	4,13%	2,07%	2,81%	6,22%	6,01%	7,24%
Fear	11,24%	13,38%	9,38%	12,50%	3,00%	6,23%	3,86%	2,66%	15,33%	6,94%	10,55%
Happiness	12,58%	8,42%	14,47%	8,04%	30,45%	5,55%	15,36%	21,86%	4,49%	14,24%	8,99%
Neutral	35,48%	27,90%	27,92%	34,60%	24,82%	37,46%	36,90%	41,43%	18,66%	30,74%	33,26%
Sadness	14,44%	9,74%	10,45%	13,58%	6,38%	13,38%	9,17%	5,58%	38,00%	11,78%	14,71%
Surprise	13,34%	35,21%	27,66%	22,05%	21,10%	29,13%	28,06%	23,11%	11,39%	26,05%	17,05%

Figure 2. Emotion probabilities for different regulatory activities

Apart from the neutral states, the most common emotion expressed by learners is *surprise*. The study of Lajoie et al. (2021) in the context of clinical reasoning shows that *angry* emotions were most prevalent in self-regulated learning, while surprised emotions were the second most frequent. We have examined the video data for multiple shared emotion segments to verify accuracy and further identify this finding difference. There might be an explanation for this in the nature of the learning tasks and collaborative learning context. While collaborating, the learners tend to have *surprised* expressions of their peers' opinions and thoughts. Interestingly, we found that *sadness* is the most frequent expression while conducting *increasing awareness* as a strategy for emotional regulation. It is important to bear in mind that caution must be applied with small sample size. Nevertheless, these findings raise intriguing questions regarding the association between emotions detected from facial expressions and learners' regulatory process. Kruskal-Wallis H Test showed significant differences in the emotion probability distributions among different regulatory activities with *p-values* = <0.001. The Chi-square test showed a significant relationship between emotional synchrony and regulatory activities in collaborative learning, X^2 (80, N = 7339) = 727.475, p < .001.

Discussion and Conclusion

This study aimed to investigate the emotional regulation process in synchronous CSCL and provide empirical evidence of how AI techniques can be utilised to inform this process. Although a considerable amount of literature has explored emotional regulation in asynchronous CSCL or face-to-face collaborative learning, much less is known about this process in synchronous online learning. While the application of synchronous CSCL in hybrid and online learning has significantly increased since the recent COVID-19 pandemic (Järvelä & Rosé, 2020), an in-depth understanding of learning regulation in this context is essential. Notably, learning regulation has been increasingly recognised as a critical factor for learners' success (Hadwin et al., 2018). However, capturing the process of learning regulation, especially emotional regulation, has been challenging due to its "unobservable" nature (Järvelä et al., 2019). The methodological issue is even more difficult to address in dynamic collaborative learning settings (Nguyen et al., 2022). Recent studies have suggested the promising role of advanced technologies such as AI in better understanding and supporting learning and teaching (Azevedo & Gašević, 2019; Cukurova et al., 2020; Nguyen et al., 2020; Perera & Gardner, 2017). This study utilised AI facial expression recognition approach to address the methodological challenge by assessing and informing about the learners' emotional regulation process in synchronous CSCL.

This study delivers a significant methodological contribution to the field of learning regulation research as it delivers an extent of change to the existing methods to a large group of audiences (Bergh et al., 2022). Our approach brings a fair degree of change to methodologies in learning regulation research by demonstrating the use of AI techniques incorporated with qualitative video analysis and process mining to examine learning regulation in collaborative learning. This study does not only provide a process-oriented view on emotional regulation in synchronous CSCL but also demonstrates a methodological approach for utilising AI technology in examining learning regulation. Furthermore, our methodological contribution would benefit a large group of scholars in the learning regulation and educational technology research communities since it responded to several recent calls for multidisciplinary efforts to make methodological progress and theoretical advancement in learning regulation research (Azevedo & Gašević, 2019; Nguyen et al., 2022).

Järvelä et al. (2020) propose that "with the aid of advanced technologies, multidisciplinary collaboration between the learning sciences, affective computing, and machine learning can help to study these complex phenomena" (p. 2392). However, prior research also emphasised the challenges related to aligning learning theories and technological aspects to utilise advanced technologies to provide new insights and further offer real-time support for learning and teaching (Azevedo & Gašević, 2019; Cukurova et al., 2020). Still, there remains a significant gap between those who understand AI's methods and techniques and those who know how learning and teaching could be improved. Additionally, there is a perceived lack of evidence about the methodological applications of AI in learning and teaching. By applying AI models as scientific tools (Baker, 2000) and socially shared regulation of learning as the theoretical framework (Hadwin et al., 2018), this study attempted to bridge the gap between AI machine learning and learning theories to establish a foundation for further design and development of AI-enhanced learning analytics information systems (LAIS).

Our findings also contribute to the literature on educational IS, which has recognised LAIS as a class of information systems and called for multidisciplinary effort bridging IS and educational research (Nguyen, Tuunanen & Gardner et al., 2021). The findings of our study shed light on the design of AI-enhanced LAIS for promoting collaborative learning regulation. Furthermore, previous discussions surrounding learning regulation indicate that a situated development of an AI-enhanced system could reveal the "invisible" processes of emotion and cognition at the core of learning regulation (Nguyen et al., 2022). We hope that this work will produce fresh insights into the development of such systems.

However, this study still has some limitations. First, as one of the early attempts to granularly examine a new methodological approach to analyse video data for learning regulation, additional effort is needed to evaluate our proposed approach's reliability and feasibility. Nevertheless, in accordance with previous studies' suggestions, we believe this methodological exploration is essential for pushing the research agenda forward. Second, although they provide useful insights into the emotional regulation process, small sample size may impact the generalizability; thus, our further work will replicate the study on a large-scale implementation.

Notwithstanding these limitations, the study certainly contributes to our understanding of the emotional regulation process in the context of synchronous CSCL. Furthermore, this work offers valuable prepositions for the methodological progress in learning regulation research with AI. Based on our work, future research could continue building predictive models for early detection of regulation in collaborative learning. Ultimately, this study seeks to establish a solid theoretical, technological, and methodological grounding for further development and implementation of human-centred AI-enhanced LAIS to support learning and teaching.

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