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Human and artificial intelligence collaboration for socially shared regulation in learning

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Abstract

Artificial intelligence (AI) has generated a plethora of new opportunities, potential and challenges for understanding and supporting learning. In this paper, we position human and AI collaboration for socially shared regulation (SSRL) in learning. Particularly, this paper reflects on the intersection of human and AI collaboration in SSRL research, which presents an exciting prospect for advancing our understanding and support of learning regulation. Our aim is to operationalize this human-AI collaboration by introducing a novel trigger concept and a hybrid human-AI shared regulation in learning (HASRL) model. Through empirical examples that present AI affordances for SSRL research, we demonstrate how humans and AI can synergistically work together to improve learning regulation. We argue that the integration of human and AI strengths via hybrid intelligence is critical to unlocking a new era in learning sciences research. Our proposed frameworks present an opportunity for empirical evidence and innovative designs that articulate the potential for human-AI collaboration in facilitating effective SSRL in teaching and learning.

INTRODUCTION

Digital platforms are increasingly part of everyday human life. With the assistance of artificial intelligence (AI), teaching and learning can also be facilitated. The educational context represents a highly specialized area of application compared to other fields in which AI can more easily be used to speed up processes and automation (Nguyen et al., 2020; Roll & Wylie, 2016). Human learners are unique in using creative and flexible thinking, expressing and interpreting effects, as well as connecting thinking and action to long-term aims, values

Practitioner notes

What is already known about this topic

- For collaborative learning to succeed, socially shared regulation has been acknowledged as a key factor.
- Artificial intelligence (AI) is a powerful and potentially disruptive technology that can reveal new insights to support learning.
- It is questionable whether traditional theories of how people learn are useful in the age of AI.

What this paper adds

- Introduces a trigger concept and a hybrid Human-AI Shared Regulation in Learning (HASRL) model to offer insights into how the human-AI collaboration could occur to operationalize SSRL research.
- Demonstrates the potential use of AI to advance research and practice on socially shared regulation of learning.
- Provides clear suggestions for future human-AI collaboration in learning and teaching aiming at enhancing human learning and regulatory skills.

Implications for practice and/or policy

- Educational technology developers could utilize our proposed framework to better align technological and theoretical aspects for their design of adaptive support that can facilitate students' socially shared regulation of learning.
- Researchers and practitioners could benefit from methodological development incorporating human-AI collaboration for capturing, processing and analysing multimodal data to examine and support learning regulation.

and purposes. More research focus is needed on the collaborative potential of hybrid intelligence that leverages the capacities of humans and machines to learn from and reinforce each other (cf. Akata et al., 2020). Since AI can assist in many routine processes, we claim that it is especially important for strengthening “very human” capabilities to (a) adapt to new situations and tasks, (b) collaborate productively and proficiently, (c) develop socioemotional skills for tackling challenging problems, and (d) have an ability to take initiative, set goals, and monitor oneself and others. We also acknowledge the pivotal role of technologies in leveraging human competencies to their full potential.

Self-regulated learning (SRL) (Winne & Hadwin, 1998) and socially shared regulation in collaborative learning (SSRL) are theoretical frameworks for explaining core human learning mechanisms, such as the metacognitive ability to monitor, regulate and adapt one's cognitive, motivational, emotional and social learning processes. Co-regulation (CoRL) refers to processes in which individuals actively engage with others to regulate their own and others' learning (Hadwin et al., 2018).

Recent advancements in learning technologies and multimodal data collection have offered new opportunities to empirically prove these phenomena (Saint et al., 2022). Both SRL and SSRL can be useful frameworks for constructing evidence-based guidelines for future human competencies as well as operationalizing theory-driven methodological opportunities for human and AI collaboration. In the present work, we refer to both SRL and SSRL as involving the concept of co-regulation, a mode of regulation, as defined by Hadwin et al. (2018). Making enhancements in collecting and examining multimodal data both efficiently and effectively requires gathering and synchronizing the diverse expertise of data scientists in learning analytics, engineering and statistics (Järvelä et al., 2020).

While leveraging a depth and breadth of cross-disciplinary expertise makes these advancements possible, it also introduces new challenges and risks arising from lines of research that become heavily data-driven and sometimes divorced from the theoretical and empirical work that has developed understandings of human learning. The aim of this paper is to introduce a conceptual framework guided by both self-regulated theory and AI methods used to advance research in human and AI collaboration. We introduce a trigger concept and a hybrid Human-AI Shared Regulation in Learning (HASRL) model to offer insights into how the human-AI collaboration could occur to operationalize SSRL research.

SSRL augments human ability to adapt

Self-regulated learning theory and related research have shown that self-regulated learners are adaptive learners who are metacognitively, motivationally and behaviourally active participants in their own learning (Schunk & Greene, 2018). In pursuing and committing to their goals, such learners implement relevant learning strategies aligned with these goals and monitor their progress toward the goals. When goal progress is inadequate, these learners engage in purposeful adaptation, thereby changing strategies and learning conditions to achieve their goals (Winne & Hadwin, 1998).

To address the increasingly collaborative nature of learning, socially shared regulation (Hadwin et al., 2018; Järvelä et al., 2018) conceptualizes regulation in social and interactive learning contexts. Consistent with SRL, SSRL also unfolds over four loosely sequenced and recursive phases, although SSRL targets the regulation of learning at the group level rather than in terms of individual regulatory processes. In the first phase, groups negotiate shared perceptions or interpretations of a given collaborative task (Phase 1). Then, groups draw on their collective awareness of task conditions, contexts and target outcomes to negotiate shared goals, standards and plans for the task (Phase 2). Groups coordinate strategic task engagement, collectively and flexibly drawing upon a range of cognitive, socio-emotional, behavioural and motivational strategies (Phase 3). Finally, groups draw on collective experiences and evaluations of those experiences to make strategic adaptations in current and/or future task planning and strategic engagement (Phase 4). Throughout these regulatory cycles, collective monitoring and evaluation emerge to guide team decision-making and the adaptation of collaborative processes, progress and products, thereby intentionally optimizing learning where needed.

Multimodal multichannel data with advanced learning technologies, a range of digital tools and platforms that are designed to enhance and augment the learning process (Azevedo & Gašević, 2019), has greatly contributed to the empirical understanding of SRL and SSRL processes (Järvelä & Bannert, 2021). A number of data modalities from different channels have been collected to investigate the cognitive, metacognitive, emotional and social processes related to learning regulation at both the individual and group levels (Fan et al., 2022; Nguyen, Järvelä, Rosé, et al., 2022). These data include eye gazes, tracking logs, as well as video, audio and physiological data such as electrodermal activity (EDA) and heart rate. Nevertheless, analyses of these multimodal multichannel SRL process data face several challenges associated with the alignment between theoretical notions, data structures and methodological assumptions underlying AI techniques used to analyse data (Azevedo & Gašević, 2019; Nguyen, Järvelä, Wang, et al., 2022).

We anticipate that methodological development in multimodal measures of SRL (Fan et al., 2022; Järvelä et al., 2022), multimodal learning analytics (Giannakos et al., 2022), combined with recent machine learning and AI-based analytical solutions (Nguyen, Järvelä, Wang, et al., 2022) has great potential to empower learners to express agency and collaborate with AI both individually and in groups. For example, AI can be used to explain how learners can monitor their own learning process and then use AI-enhanced tools to help them to externalize, invite and share regulation. However, this work is in its infancy because the field lacks the metrics necessary to operationalize the related theory, data and AI-based methods (Luckin & Cukurova, 2019).

Trigger concept framework for SSRL

SSRL entails a complex adaptive mental process. To leverage multimodal data sources, which require metrics to be empirically investigated with multiple data channels, analysis with AI-based methods needs to be operationalized to support advanced learning technologies. The problem is that methodological advancements (Saint et al., 2022) for triangulating and synchronizing multimodal data have not been theoretically guided by SRL and SSRL. We have been working on developing an empirically testable model of trigger events as a conceptual framework for advancing research about regulation within complex individual and collaborative learning situations. Building on Winne and Hadwin's (1998) SRL and Hadwin et al.'s (2018) SSRL theories and supported by recent empirical research, we have empirically identified specific types of events (which we call triggers) that invite regulatory responses in collaborative learning (Haataja et al., 2018; Järvelä et al., 2022, 2023; Sobocinski et al., 2020; Vuorenmaa et al., 2022). This trigger-based framework provides a theoretical direction for advancing research about regulation during complex learning in both individual and collaborative learning contexts which guides empirical identification where regulation happens or not. In evolving collaborative learning process multimodal data collection can help researchers to detect signals of those cognitive, emotional, motivational, or social sources existing in collaborative learning (eg, Lobczowski, 2020) which invite group members for regulatory processes. For example, Haataja et al. (2018) recognized physiological synchrony among the collaborating students as an indicator for trigger events in cognitive regulation, while Sobocinski et al. (2020) used coded video data of collaborative interactions and physiological state transitions in the heart rate to identify adaptive regulation or maladaptive behaviour in collaborative learning. Likewise, Nguyen, Järvelä, Rosé, et al. (2022) showed evidence for how shared physiological arousal events indicated regulatory trigger events in SSRL. In the present framework (see Figure 1) we position the role of multimodal data to identify trigger signals from *various sources* in collaborative learning situations that can be used to *detect triggers* for (S)SRL, thereby providing metacognitive markers for the regulation of cognition, motivation, emotion and behaviour. We posit that leveraging multimodal methodologies and a range of analytical methods to detect these regulation opportunities provides a useful framework for identifying *SRL traces, sequences, patterns and models*. These analyses complemented with other kinds *contextual information*, eg, situated

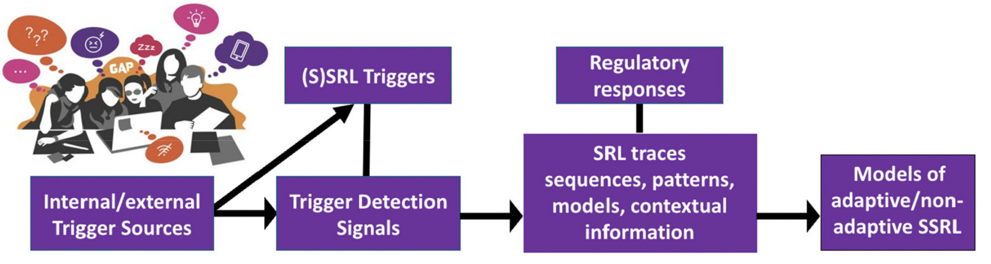

FIGURE 1 Trigger concept framework in researching SSRL with multimodal data.

self-reports or interviews can help to compare situations when *adaptive and maladaptive* regulatory responses follow those triggers.

Previous studies have highlighted that the AI technology used within education and training must be designed with the understanding of teaching and learning in mind (Luckin & Cukurova, 2019). Our understanding of learning processes and effective teaching practices has been enhanced by interdisciplinary research within the learning sciences. Such an understanding is also essential for designing and utilizing AI in supporting learning and teaching. Thus, we propose the trigger concept framework to assist AI developers in gaining a better understanding of SSRL processes. One of the major challenges in utilizing advanced technologies for supporting regulation in learning is to integrate the theoretical and technological aspects (Azevedo & Gašević, 2019; Nguyen, Järvelä, Wang, et al., 2022). Since AI with state-of-the-art computational techniques can be used to gain insights into the "black box" of the learning processes (Spikol et al., 2018), the trigger concept framework outlines the key aspects of SSRL for technology developers to design AI-enabled solutions to examine, predict and assist SSRL in collaborative learning. Furthermore, the trigger concept framework directly responds to a recent call for a reinterpretation and postulation of new frameworks, views and theories in response to the lack of alignment between conventional theories and advanced technologies mediated by new learning experiences (See this special issue). Trigger concept as the novel theoretical framework allows for aligning SSRL with advanced technologies such as AI to promote human-AI collaboration for advancing (S)SRL research toward human-AI shared regulation in learning.

Human-AI collaboration for advancing (S)SRL research using the trigger concept

In this paper, we argue that human-AI collaboration is essential for the progression of SSRL research in the age of AI. The synthesis of collaboration between humans and AI with the involvement of integrated hybrid intelligence is desirable for improved overall effectiveness. As the name implies, hybrid intelligence is a combination of human and machine intelligence for the purposes of expanding human intelligence instead of replacing it with AI machines. Hybrid intelligence aims to integrate AI agents with humans by taking into account human expertise and intentionality (Akata et al., 2020). Hybrid intelligence approach shows noticeable potential to advance current theories and practices across many domains including education. For example, Holstein et al. (2020) identify a general set of dimensions to capture hybrid human-AI adaptations and illustrate how hybrid human–AI approaches can be used to characterize prior work in education and envision new possibilities. Nevertheless, in order to transform the use of AI in learning toward hybrid intelligence, it is imperative that researchers go beyond the ordinary to generate the knowledge and information needed to shape AI in learning (Roschelle et al., 2020). However, to date, little is known about how researchers should collaborate with AI and integrate the forces of AI and human intelligence for advancing research in learning sciences.

In the context of (S)SRL research, AI has enabled promising facilities for better understanding and supporting learning regulation (Molenaar, 2022; Nguyen, Järvelä, Wang, et al., 2022). Specifically, these approaches have enabled the analysis of the multi-level and multifaceted characteristics of regulation in collaborative learning (Ouyang, Wu, et al., 2023; Ouyang, Xu, et al., 2023). In the past, the complexity and dynamics of collaborative learning often required researchers to examine different facets of regulation separately. Although prior studies have offered valuable insights into (S)SRL processes, there is a recent call for more synergistic analysis approaches combining different facets of regulation (Nguyen & Järvelä, 2023). Recent studies have been able to address this need by using AI-driven approaches for multi-channel sequence analysis to examine multifaceted, adaptive and temporal characteristics of regulation in collaborative learning (Ouyang, Xu, et al., 2023). However, the integration of AI into (S)SRL research and support development has still faced several challenges related to the alignment between the theoretical and technological aspects of human-AI interactions (Hwang et al., 2020). The interplay between human and AI should be examined to offer insights into how human-AI collaboration can be used to increase awareness about (a) the presence of these critical trigger moments, (b) adaptive regulatory response options, and (c) recurrent maladaptive regulation patterns in response to such triggers. Accordingly, advanced the development of a human-AI shared regulation in the learning model to inform (S)SRL research and the identification of AI affordances for advancing SSRL research. We later demonstrate a research case as an example of how human-AI collaboration could advance SSRL research and then provide propositions for human-AI collaboration for SSRL in learning.

Human-AI shared regulation in learning (HASRL) model

Substantial multidisciplinary efforts will be needed to bridge the gaps between the technical and theoretical components of human-AI collaboration to advance (S)SRL research (Nguyen & Järvelä, 2022). However, it is often challenging to establish a common language and understanding about both human learning and AI machine learning operations across different disciplines. To address these issues, based on the trigger framework, we have developed a hybrid human-AI shared regulation in learning (HASRL) model (see Figure 2) to illustrate the interoperation and interplay between the human and AI regulatory system as two subsystems of a hybrid intelligent system.

HASRL explains human-AI regulation by modelling the interactions between the centre (S)SRL components explained by the trigger framework according to the fundamental functions

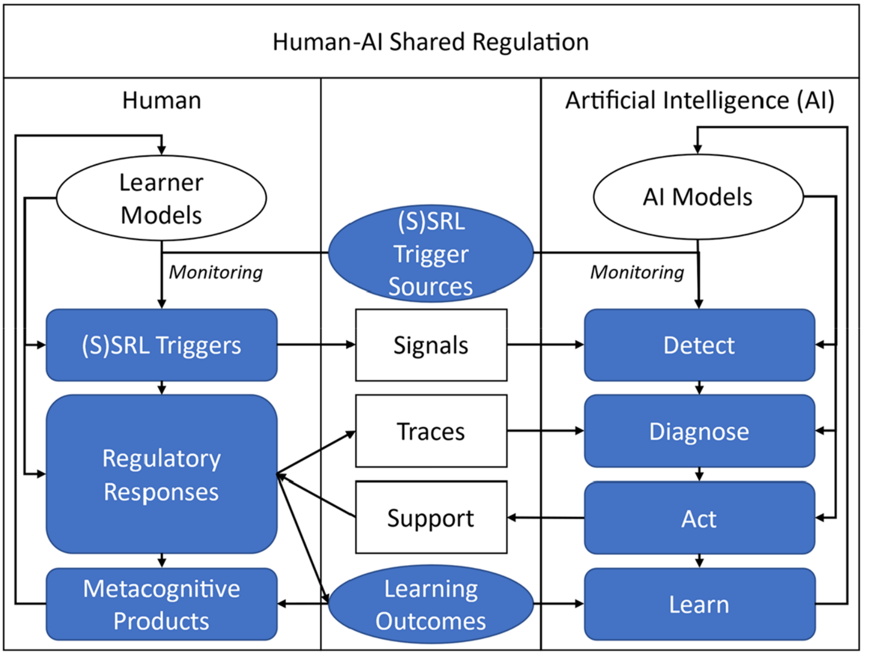

FIGURE 2 Human-AI shared regulation in learning (HASRL) model.

of AI. The (S)SRL triggers are facilitated by the internal and external trigger sources while being detected by the AI models via SRL signals. Human (S)SRL processes are operated by mental models that could be described as cognitive conditions in the COPES model (Winne & Hadwin, 1998). In addition, learner models comprise emotional mental models that are intrinsically tied to cognitive models (Stangl, 2012). AI diagnoses human (S)SRL responses via (S)SRL traces (eg, sequences, patterns, etc.) and acts to support those responses. The appropriate regulatory responses lead to better learning outcomes that can be observed by both humans and AI. We argue that learners eventually develop their (S)SRL competencies through metacognitive products by reflecting their regulatory responses and learning improvement.

Recent augmentation perspectives of artificial intelligence in education (AIED) have emphasized the role of AI in supporting and collaborating with human learners and teachers rather than replacing them. Accordingly, a human-AI shared regulation system should be designed to optimize human strengths while compensating for weaknesses. The conditional automation of AI has been recommended for the incorporation of human and artificial intelligence while preserving sufficient human control. Molenaar (2022) describes the detect-diagnose-act framework as the basic functioning of AI in education. Detect stands for the learning process data, physiological data such as skin conductivity or contextual data such as video data collected input for AI. The data will be diagnosed to determine the learner's current state and predicted future development. With the help of “AI-diagnosis” scaffolds, support and teachers' acts can be made for learners. However, it could be argued that the development of human (S)SRL skills would be hindered by AI support due to the potential eventual growth of reliance on AI systems. Therefore, we argue for the development of learnable AI systems. These systems should not only respond to the trigger sources but also adjust AI models to scaffold human regulatory competencies. As a result, we describe AI regulatory subsystems with the basic detect-diagnose-act functions of AIED as well as the learning component. The HASRL model offers a high-level conceptual architecture for connecting technology developers and learning scientists to facilitate the development of AI-enabled solutions for supporting SSRL.

Human-AI collaboration in SSRL research

AI affords the advancement of SSRL research with novel techniques and methods for unfolding the previously “unobservable” metacognitive-level aspects of SSRL (Järvelä, Malmberg, Sobocinski, et al., 2021). AI has allowed for novel approaches to utilizing multimodal SSRL data obtained from numerous channels including digital traces like log data (Cho & Yoo, 2017), eye gazes (Taub & Azevedo, 2016), or physiological measures (Nguyen, Järvelä, Rosé, et al., 2022). For example, AI machine learning models offer promising data processing at scale, as well as sophisticated analysis and predictive capabilities (Nguyen, Järvelä, Wang, et al., 2022; Sharma & Giannakos, 2020). While recent studies have made partial progress in incorporating AI into research to explore and support students' self-regulation (Fan et al., 2022), there has been little discussion about how AI could facilitate advancements in SSRL research. Appropriately, we reviewed potential AI capabilities and have categorized them into three key AI affordances for human collaboration in SSRL research as follows: (1) *extracting characteristics and detecting micro-behaviours*; (2) *automating tasks for efficiency and granularity*; and (3) *operating complex and sophisticated analyses*.

Extracting characteristics and detecting micro-behaviours could be done by using AI to better understand SSRL. Interpersonal affective and emotional exchanges between group members serve to shape a group's perceptions of emotions and the group's socioemotional climate (Volet et al., 2009), influencing an internal condition that frames how individuals or groups engage in regulatory processes and as a product of the learning environment (Bakhtiar et al., 2018). Previous studies have not only produced capabilities to automatically detect cognitive and emotional activities in real-time but have also demonstrated that the objective measurement and classification of these deep learning behaviours is possible. For example, Yang et al. (2019) have applied deep learning principles to representations of the features of an electroencephalogram (EEG) to offer a solution for measuring cognitive workload. The proposed recognizer involved a feature-mapping layer in a stacked denoising autoencoder (SDAE) that was able to capture and maintain information in EEG dynamics to detect human mental workload. Furthermore, a review by Debie et al. (2019) established that cognitive activities can be objectively assessed by using data collected from different modalities including EEG, electrocardiography (ECG) and eye-tracking. Likewise, research has proven that the application of deep learning on various media could effectively recognize human emotions including micro-expressions (Pfister et al., 2011; Tzirakis et al., 2018; Zhao et al., 2011). An example is the work of Zhao et al. (2011) on facial expression recognition using near-infrared videos. Feature fusion using deep learning methods on data from multiple modalities enables the further enhancement of the accuracy of detecting and assessing human cognitive and emotional activities (Tzirakis et al., 2018; Yin et al., 2017). Since cognitive and emotional activities are at the core of learning regulation, advanced techniques, and their capabilities are able to offer novel insights into the learners and their SSRL. These activities also provide a critical platform for calibrating timely human awareness of these emotional activities.

Automating tasks for efficiency and granularity with AI capabilities would allow for the processing and analysing of multimodal SSRL data at scale. Capturing multimodal “big” data has provided exclusive opportunities to investigate SSRL processes more thoroughly (Järvelä, Malmberg, Haataja, et al., 2021; Malmberg et al., 2017), yet learning scientists and researchers have faced several challenges in advancing the use of such multimodal “big” data. Data integration and processing are often time-consuming and expensive, especially when data granularity is retained for sophisticated analysis. In fact, despite the preservation of the granularity of some data modalities such as physiological signals and log data being relatively uncomplicated, data granularity is often sacrificed in favour of the ease of video and audio data processing. Fortunately, AI could enable the automation of data processing tasks with superior efficiency and granularity. For example, AI can automatically generate “good enough” transcripts as a first step in the transcription of audio-recorded data, offering time and cost advantages (Bokhove & Downey, 2018). By adopting AI-automated tasks, processing a massive amount of data at high granularity could be feasible. While it is still imperative to triangulate and combine data with different granularities for SSRL research to progress (Järvelä, Malmberg, Haataja, et al., 2021), we argue that retaining a granular level of integrated “big” data will shed new light on understanding and supporting SSRL.

Operating complex and sophisticated analyses on the multimodal “big” data about SSRL could be accomplished using AI machine learning techniques. Learners' regulatory activities and their development over time can be better recognized, predicted and improved by using AI techniques (Järvelä & Bannert, 2021; Molenaar et al., 2021). For instance, AI machine learning models have previously been reported as able to predict interactions for SRL (Molenaar et al., 2021; Sabourin et al., 2013), SSRL (Nguyen, Järvelä, Wang, et al., 2022) and learning performance (Di Mitri et al., 2017). Analyses of multimodal data with AI machine learning techniques might be useful in addressing challenges associated with violating traditional statistical assumptions (eg, independence) (Azevedo & Gašević, 2019). AI machine learning also allows for the utilization of multimodal data about SSRL collectively (Nguyen, Järvelä, Wang, et al., 2022). It is expected that the rapid development of AI and sensor technologies will further enable us to better understand how SSRL progresses over time and to provide real-time and adaptive scaffolding and feedback to address learners' regulatory needs.

RESEARCH CASES—SOCIALLY SHARED REGULATION OF COMPLEX LEARNING PROCESSES IN GROUPS

By way of illustration, we present an experimental study as a research case to demonstrate how human-AI collaboration could leverage the proposed trigger concept to advance SSRL research.

Experimental design with trigger concept

In this case, trigger events are conceptualized as disruptive incidents causing challenges for collaborative learning. The study involved small groups of high school students ($N=82$), three students in each group, working on a collaborative task. The aim of the task was to design a healthy smoothie. Cognitive and emotional triggers were intentionally introduced as experimental group treatments. The cognitive trigger was a customer informing the team of an allergy to latex protein and dairy products. The emotional trigger was an angry customer interrupting and pressuring the team to speed up the process. Figure 3 illustrates the experimental design for this study.

Multimodal and multichannel data were captured for trigger-detection signals. The 360-degree camera and individual microphones were used to procure a full observation of the group collaboration. High-resolution and -sampling rate video and audio recordings were obtained to allow both humans and AI to identify trigger-detection signals such as content, tone of utterance, physical gestures, or eye gaze. Physiological sensors were utilized to record EDA and heart rate (HR) data for assessing learners' physiological activation and synchrony as trigger-detection signals. Furthermore, situated self-reports were implemented to measure students' emotional valences, task interest, mental efforts and confidence judgements.

While some research has been carried out on triggers for regulation in collaborative learning (Nguyen, Järvelä, Rosé, et al., 2022), no controlled studies have been reported. The existing accounts of identifying trigger events in collaborative learning are limited. The recognition of regulatory triggers is essential for advancing the current understanding of collaborative learning regulation and designing appropriate and effective support for learners. This experimental setting (illustrated in Figure 4) with multimodal data collection and controlled

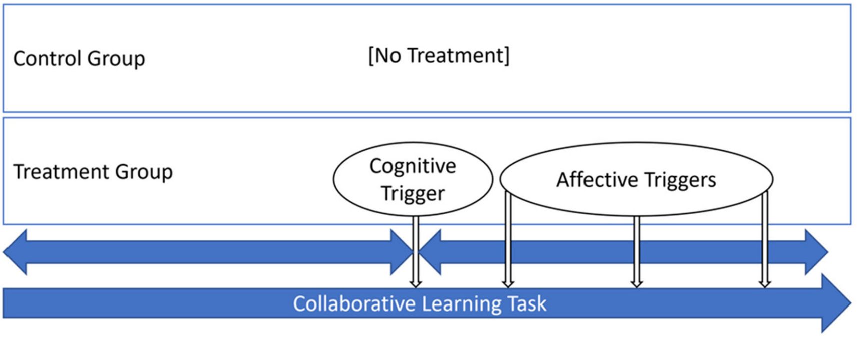

FIGURE 3 Experimental design with regulatory triggers.

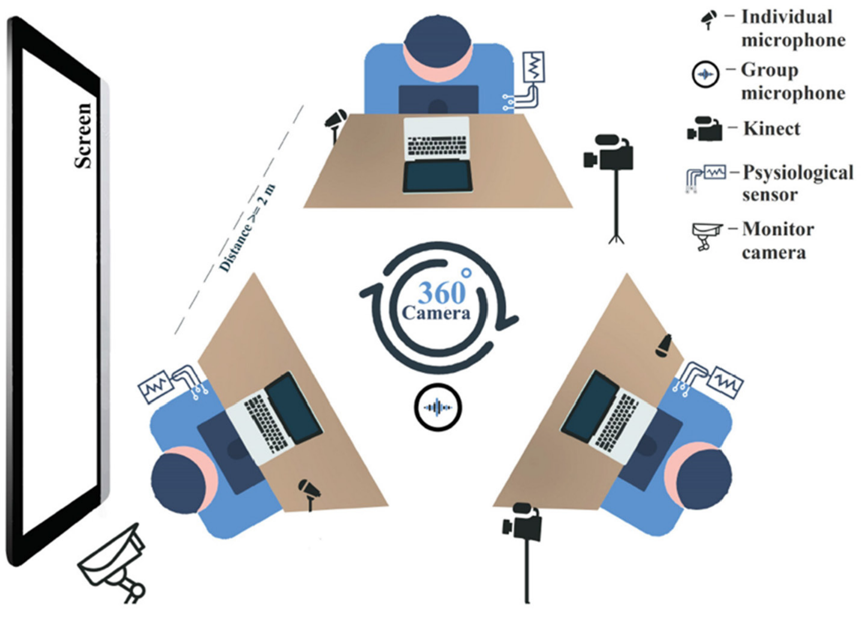

FIGURE 4 Experimental setting.

regulatory triggers as experimental treatments allowed for an in-depth investigation into the temporality and dynamics of (S)SRL in collaborative learning.

Figure 5 demonstrates an example of a learner's EDA around the regulatory triggers in one treatment group. The learner's physiological activation was raised slightly after the cognitive trigger and noticeably surged after the first emotional trigger. Previous studies have recognized the use of physiological signals in examining the regulatory activities of learning (Haataja et al., 2018), especially in collaborative learning settings (Dindar et al., 2022; Nguyen, Järvelä, Rosé, et al., 2022). Nevertheless, most SRL research studies have only been carried out with the interval-related analysis of physiological signals to estimate the triggering moments by triangulating with other data modalities (Järvelä, Malmberg, Haataja, et al., 2021). It has proven challenging to identify triggering moments using only inductive analytical approaches using event-related analysis of physiological signals. Therefore, the experimental design with the controlled treatments for triggering SSRL allowed for the determination of the exact moments of trigger sources to examine the regulatory responses on different types of regulatory triggers.

Extracting emotional expression in SSRL research: A case example

Although identifying regulatory triggers and responses is essential for providing timely regulatory support, the emotional and cognitive processes at the core of regulation are often unobservable by humans and difficult to trace using traditional approaches (Järvelä & Bannert, 2021). This case example from the same experimental study demonstrated the utilization of AI to extract emotional expression to advance SSRL research among the groups with both cognitive and emotional triggers.

In order to examine the emotional regulatory responses, it is desirable to detect the types and alignment of continuous emotional valences and discrete affective states among the learners. However, the manual recognition of emotion from facial expressions requires

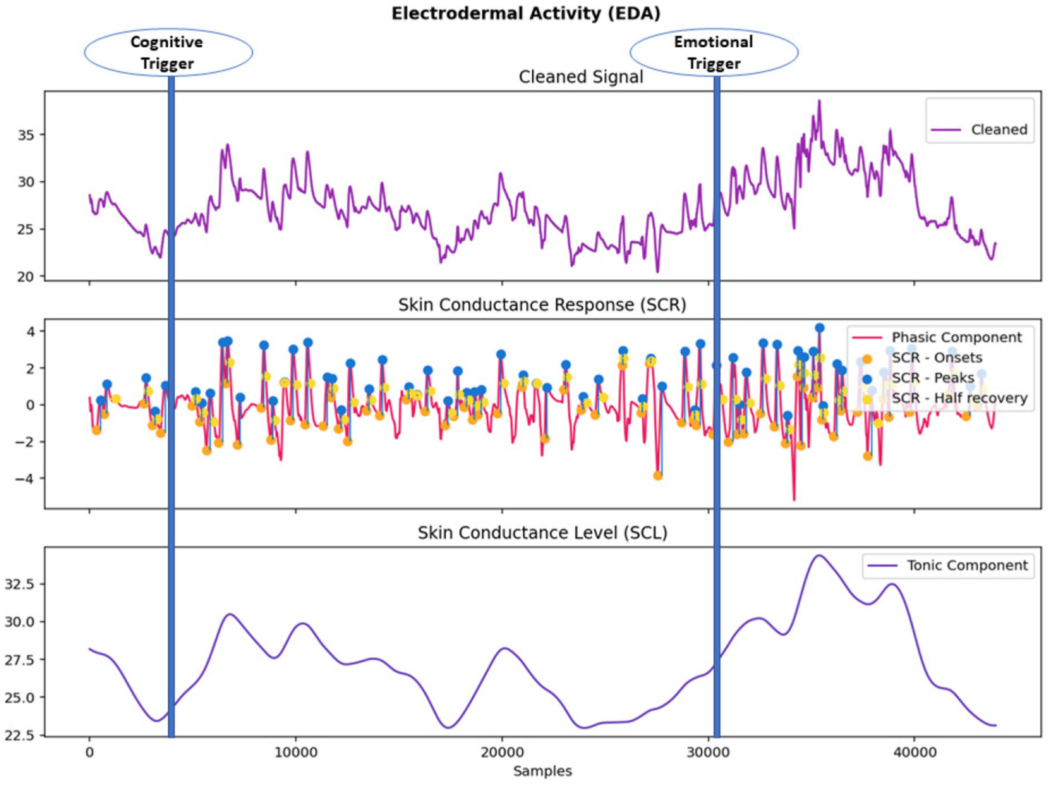

FIGURE 5 Example of a learner's electrodermal activities (EDA) around the regulatory triggers.

physiological expertise and consistency in judgement; this process is also extremely time-consuming. Meanwhile, the development of AI has offered effective pre-trained models for facial expression recognition to reveal information regarding a person's emotional state. In this example, to recognize emotions from facial expressions, face detection was conducted using dlib tools, and then the EmoFAN model was used with two units, followed by five convolutional layers and a fully connected layer (Toisoul et al., 2021). The continuous emotional valences and discrete emotions of four categories (neutral, happy, negative and surprised) were obtained and aligned among the members in each group so that their affective states could be analysed.

Figure 6 shows the distribution of emotion over time before and after each trigger (CT = cognitive trigger; aggregated across group members). A noticeable increase in *negative* emotions was observed after the first and second emotional triggers. This could indicate the role of the emotional triggers in pushing the groups to complete their task early. Nevertheless, a rise in *positive* and *surprised* emotions was noted toward the end of the collaborative learning task. This may be explained by the fact that the participants were happy with their products and had been waiting for the allotted time to end. Further research could investigate the effects of different types of affective triggers. Nevertheless, the extracted facial emotions inform about the emotional progress of learners and their synchrony throughout the regulatory triggers for SSRL (Nguyen et al., 2023). This example illustrated how AI allows for extracting new features to advance our understanding of SSRL.

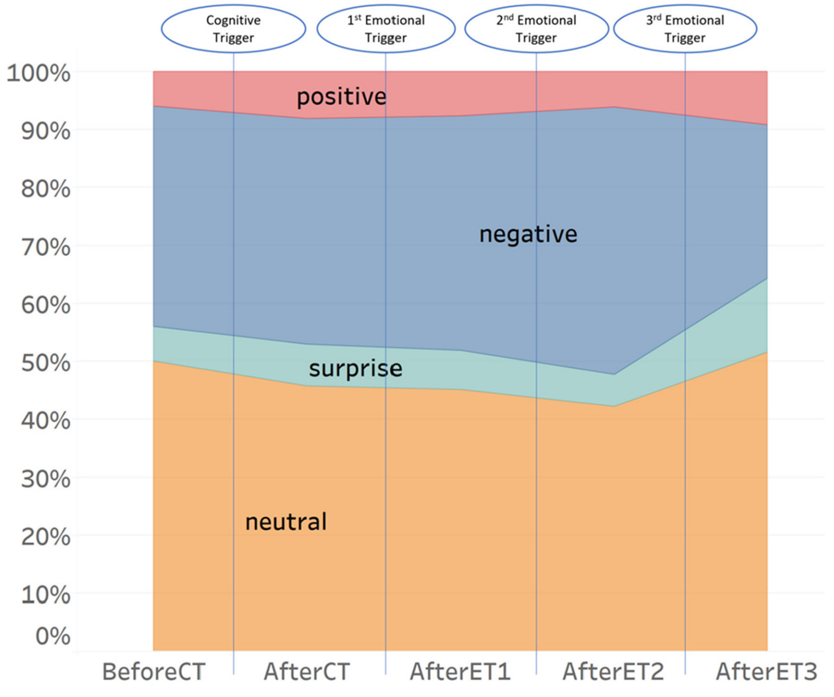

FIGURE 6 Emotion distribution over time before and after each trigger.

Human-AI collaboration for efficient pre-processing and granular analysis: A case example

In this case example, we present an AI-human collaboration approach for studying SSRL with an AI-enabled micro-analytical recording technique for granular qualitative video analysis. We demonstrate the important roles of both humans and AI in the collaboration to propose novel opportunities for advancing SSRL research. Overall, while AI could provide the capabilities necessary for processing and analysing SSRL data in high granularity at scale, researchers are irreplaceable when it comes to interpreting emotions in context and the nuances of social interactions in collaboration. We argue for bridging human-readable and machine-readable information so that both traditional and innovative analytical methods can be better incorporated with one another. Furthermore, synchronization at a granular level is essential for synthesizing the analytical powers of these methods.

This case example draws on the methodological progress made in human-AI collaboration in terms of integrating and analysing multimodal data consisting of video and audio to observe the collaborative learning process and physiological data to monitor learners' physiological activities. Data triangulation using multimodal data with recorded video, audio and physiological data has provided valuable insights into the temporality and adaptability of (S)SRL (Järvelä, Malmberg, Haataja, et al., 2021). Nonetheless, the integration of data from different modalities often trades granularity for practicality with constrained time and resources. The strong tradition of microanalytical methods for studying collaboration, such as conversation and interaction analysis (Lund & Suthers, 2018), allows for a close examination of SSRL and the learning context. However, it is challenging to record these microanalytical results in machine-readable ways while retaining their granularity. As a result, prior studies often depicted qualitative information in a certain time interval to incorporate it with other data modalities and analytical methods (Nguyen, Järvelä, Wang, et al., 2022).

Figure 7 demonstrates an example of human-AI collaboration processes compared with traditional research processes for conducting video analysis. To address the temporality of SSRL, video analysis must preserve the time dimension of the research data to explain the sequences of learning actions and regulatory behaviours. In the traditional SSRL research process using video analysis, the video and audio data must be segmented into equal intervals for analytical consistency. Moreover, it would be extremely time-consuming to record utterances with the exact time points in seconds or milliseconds. Likewise, the transcription of data for collaborative learning is often omitted due to the extensive resources required. While these tasks are tedious for human researchers, AI can automate the segmentation and transcription processes proficiently and efficiently. For example, AI allows for automatically segmenting the speech by utterances with granular starting time and ending time in milliseconds and recognizing participating (speaking) learners. This granular segmentation process can be exhausting to human despite the fact that granular segmentation is essential to integrate with other data modalities such as physiological signals. In the example depicted in Figure 7, similarity testing was conducted by using the difflib python library to compare text sequences between the raw auto-transcribed texts and the transcribed texts corrected by the researchers. The results showed fair accuracy in terms of the auto-transcription, with the similarity score being 81.46% of the total 6111 utterances. Although the results did not reach absolute precision in many cases, they were sufficient as a first step toward fine-grained segmentation and transcription.

The proposed approach provided the opportunity for recording microanalytical qualitative information with fine-grained granularity for multi-temporal consideration as well as for integration with innovative analytical methods. Figure 8 demonstrates an example of granular analysis facilitated by this approach for examining social interactions after a cognitive regulatory trigger. In this example, the learning group immediately reacted to the regulatory trigger with positive socio-emotional interactions. Then, their regulatory response was reflected

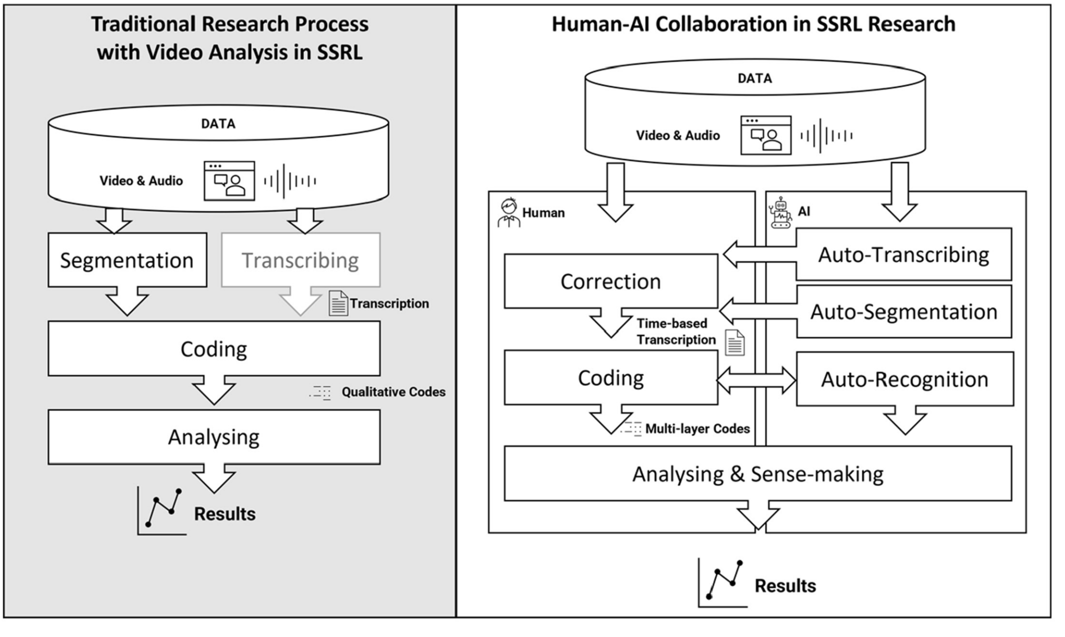

FIGURE 7 Example of human-AI collaboration process in SSRL research.

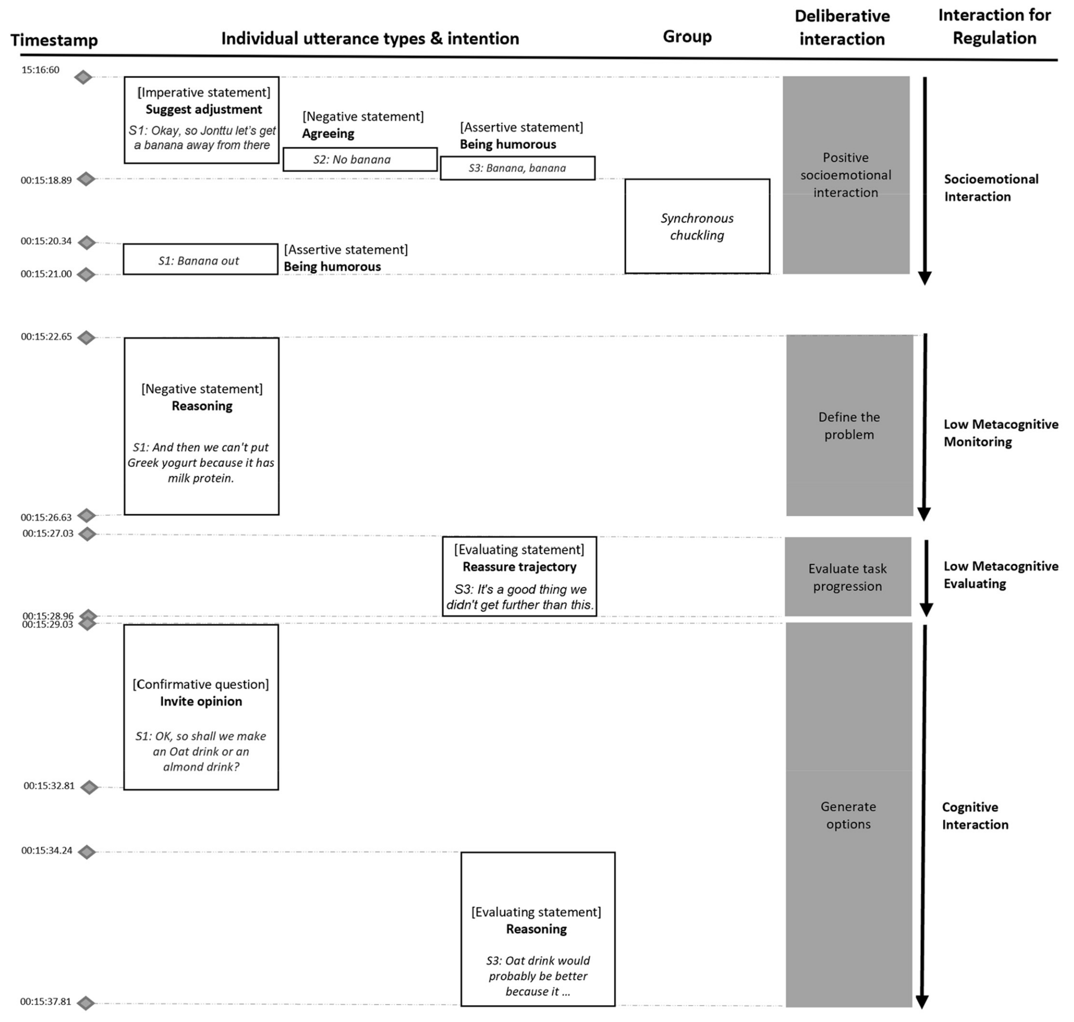

FIGURE 8 Example of granular analysis facilitated by human-AI collaboration for examining social interactions after the cognitive regulatory trigger.

through the process of problem identification, progress evaluation and option generation. The sequences of interactions were documented and qualitatively coded at both the individual and group levels for utterances with exact beginning and ending timepoints provided. Each individual utterance was examined and classified according to types of sentences and intentions (Panther & Köpcke, 2008), while the interactions for regulation and deliberative interaction types were identified at the group level (Dang et al., 2023).

Process-oriented analysis (Järvenoja et al., 2015) was then employed to unfold the interplay between types of interactions and regulatory responses. The fine-grained time dimension also allowed for the consideration of time latency in the analysis to advance the understanding of SSRL processes. Furthermore, recorded qualitative information could be aligned and integrated with AI-readable features from the multimodal dataset such as video image pixels, audio signals and physiological signals. The granular analysis of social interactions not only reveals insights into the learning regulatory processes but also informs and provides labelled data for training AI models for making sense of, diagnosing and augmenting human learning (Nguyen, Järvelä, Wang, et al., 2022). However, despite its advantages, granular interaction analysis is extremely time-consuming, and scaling the analysis to provide enough training data for AI is challenging and costly. Thus, the AI "collaboration" with humans for automating resource-demanding tasks such as segmenting and timing utterances will greatly benefit the granular analysis of SSRL at scale. We argue that combining the power of human qualitative analytical interpretation with the automated analysis of AI-readable features signifies a major step for advancing SSRL research in ways that can inform the development of SSRL support for empowering adaptive learners.

Toward human-AI collaboration for SSRL in learning and teaching

In this paper, we have positioned AI as an intelligent agent in human-AI collaboration for SSRL in learning and teaching. Recently, the concept of hybrid human-AI regulation has been proposed in the form of hybrid systems combining artificial and human intelligence to support learners' individual SRL (Molenaar, 2022). In the context of collaborative learning, we argue that effective human-AI collaboration is essential for not only promoting learners' individual SRL but also influencing SSRL at the group level toward collaborative learning success. Stepping beyond the role of AI as an intelligent tutor supporting individual learning, we propose that AI can work with learners to facilitate SSRL by detecting challenges, sense-making and recommending actions in real-time. The proposed HASRL model outlines the theoretical foundations for designing such intelligent agents for SSRL.

Traditional Intelligent Tutor Systems (ITSs) have been designed and developed to optimize the learning trajectory of each individual learner (Baker et al., 2021). Personalized and adaptive support can be provided to address individual learners' needs via the deployment of intelligent learning technologies using learning analytics and AI techniques. Recently, there has been increasing interest in developing ITS to support learners in collaborative learning settings (Haq et al., 2021). However, most ITS are designed for computer-mediated collaborative learning in digital environments since the learning processes can be easily captured via learners' digital traces. In such learning environments, learning intervention through the interactions of the intelligent agent could be provided more conveniently in digital forms. It remains challenging to capture, analyse and intervene in collaborative learning processes in real-time in authentic learning settings in open-space environments due to the data's noise and multimodal nature (Nguyen, Järvelä, Wang, et al., 2022).

Recent developments in AI including multimodal deep learning and socially assistive robots (SARs) (Winkle et al., 2019) have enabled AI capabilities to aid humans during social interactions in the open-space environment. While automation has been one of the most important drivers of robotics development, SARs focus on human augmentation via intelligent and socially interactive machines. We argue that such collaboration between learners and educational SARs could support the development of learners' SSRL skills and empower human learning in open-space collaborative learning settings. Nonetheless, the development of such SARs must consider learning theories to effectively enhance human learning rather than produce dependencies on technologies.

One direction future research on human-AI collaboration in learning and teaching could be leveraged is extending SSRL in multi-realities. Virtual, mixed and augmented reality technologies enable interaction with various degrees of virtual content in cyber- and metaverses seamlessly integrating human senses with multiple concurrent realities, whereas SSRL augmentation can enhance the collaboration with virtual assistants and provide capabilities that go beyond normal interactions. These solutions could be helpful in interprofessional education, such as healthcare teams (Jallad & Işık, 2022).

Nevertheless, it is important to note that AI cannot replace human teachers entirely. Teachers with unique human skills such as empathy, compassion and interpersonal communication abilities play an irreplaceable role in learning and teaching. These skills enable teachers to deeply understand their students' individual needs, provide emotional support and encouragement and foster a positive learning environment. Accordingly, we argue that future human-AI collaboration should not only provide direct support to learners but also involve and empower teachers in their pedagogical practices. Despite learning analytics and AI having demonstrated benefits in supporting teachers with actionable insights (Nguyen et al., 2021), sustainable efforts are needed to examine the extent to which these technologies can be extended to support teachers in complex collaborative learning environments (Mavrikis et al., 2019).

Regarding AI automation, human work being performed by machines and increasing dependencies on technology are the subjects of ongoing debate (Matarić, 2017). The dilemmas often centre around economic values and human development and well-being. In the context of learning regulation, the automatic detection of (S)SRL triggers and recommendation of (S)SRL strategies may improve the situated learning performance but also potentially hinder learners' ability to self-monitor their learning processes. If AI could effectively monitor learning and intervene for necessary correction, learners would eventually rely on AI oversight for effective learning. Accordingly, AI as intelligent agents should not only deliver SSRL support through the automation of tasks but also provide scaffolding for productive reflection. Previous studies have shown that learners' use of self-regulatory strategies increases when scaffolding is provided by the intelligent agent (Duffy & Azevedo, 2015; Wu & Looi, 2012). Nevertheless, to date, there have been few guidelines for creating intelligent agents for scaffolding SSRL. Our proposed HASRL model outlines key elements for consideration in the design and development of such AI systems for human-AI collaboration in learning and teaching.

FINAL REMARKS AND FUTURE DIRECTIONS

To conclude, our study set out to present a conceptual framework that is driven by both SSRL theory and AI methods for advancing research in SSRL and promoting learning and teaching through human-AI collaboration. We have identified key AI affordances for SSRL research and demonstrated empirical examples of how humans could collaborate with AI in advancing the field. We argue that combining the powers of humans and AI will create unique values for better understanding and enhancing human learning. Furthermore, human-AI collaboration in SSRL research with multidisciplinary joint forces will facilitate empirical evidence and design work to articulate human-AI collaboration for SSRL in learning and teaching.

The current study raises a critical question on the potential utilization of human-AI collaboration in offering novel methodological approaches to examine socially shared regulation of learning (SSRL). Considerably more work will need to be done to determine the synergistic nature of cognitive, emotional and motivational processes in learning regulation. To enhance the efficacy of AI in learning regulation research, it is crucial to develop a systematic understanding of various AI techniques and data channels for assessing one or more aspects of learning regulation. Moving forward, future research should focus on investigating the optimal ways in which human-AI collaboration can be leveraged to advance SSRL research with reduced biases and increased actionable insights for both learners and teachers.

Further research efforts could be directed towards investigating the different temporalities of human-AI shared regulation in learning. Specifically, the short-interval and long-interval cycles of SSRL could be usefully explored in further research with our proposed Human-AI approach. By examining the temporal aspects of SSRL, researchers can gain a more comprehensive understanding of how the human-AI collaboration could be leveraged to support learning regulation across different stages of learning. Additionally, these findings can offer valuable insights into how humans and AI can effectively synchronize their regulatory activities over different time intervals, thereby enhancing the overall effectiveness of the SSRL process. As a result, learning analytics tools could be designed and developed to effectively facilitate SSRL for learners and enable teachers to promote their students' SSRL and enhance their pedagogical practices.

Finally, as the field of SSRL research continues to evolve, interdisciplinary collaborations that combine the expertise of researchers from different fields such as psychology, education, computer science and engineering will be increasingly important to unlocking the full potential of human-AI collaboration for SSRL. By pooling their knowledge and expertise, these researchers can collectively identify new research questions, explore novel methodological approaches, and develop more sophisticated AI techniques for assessing and supporting learning regulation. By applying these research findings to the classroom, teachers can leverage socially shared regulation among their students, ultimately fostering stronger regulation and collaboration skills that are essential for academic and lifelong achievement. Interdisciplinary collaborations that integrate the strengths of humans and AI have the potential to transform the field of SSRL research and advance our understanding and support of learning regulation. By working together, researchers and educational technologists can harness the power of AI to analyse and optimize learning processes, while also ensuring that these tools are ethical, equitable and effective for all learners.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest regarding this study to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ETHICS STATEMENT

This research was approved by the Ethics Committee of Human Sciences of the University of Oulu and complied with the university research integrity and ethics guidelines.

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