

Exploring the interaction of cognition and emotion in small group collaborative discourse by Heuristic Mining Algorithm (HMA) and Inductive Miner Algorithm (IMA)

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Received: 29 August 2022 / Accepted: 8 March 2023 / Published online: 24 March 2023 © The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2023

Abstract

This study explored the interaction between cognition and emotion in blended collaborative learning. The participants (n=30) of this study were undergraduate students enrolled in a 16-week course on information technology teaching. These students were divided into six groups of five people each. The behavior modes of the participants were analyzed using a heuristic mining algorithm and inductive miner algorithm. Compared with the groups with low task scores, the high-scoring groups exhibited more reflection phases and cycles in the interaction process and thus more frequent self-evaluation and regulation behavior for forethought and performance. Moreover, the frequency of emotion events unrelated with cognition was higher for the high-scoring groups than for the low-scoring groups. On the basis of the research results, this paper presents suggestions for developing online and offline blended courses.

Keywords Collaborative learning \cdot Distance education and online learning \cdot Self-regulated learning \cdot Process mining

1 Introduction

COVID-19 has had a major influence on people's lives and has affected education and teaching in colleges and universities. To maintain the continuity of the learning process, colleges and universities have begun to rely on online platforms. Online platforms have been used to conduct online teaching activities, ensuring the quality of teaching during the COVID-19 pandemic. Blended collaborative learning is a crucial learning

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method in online teaching. There were many researchers focuses on the learners' cognitive development in blended collaborative learning (Lim & Lim, 2020; Rahimi & Fathi, 2021; Zheng et al., 2020), as well as the emotion development of learners (Volet et al., 2019; Mänty et al., 2020). During the collaborative learning, learners are supposed to detect the emotional states and cognition level of group members, and regulate their learning process and emotion to identify and address cognitive, motivational, emotional and social challenges. Regulating cognition and emotion of learners successfully in the collaborative learning can enhance learners' knowledge construct, comprehensive learning, and critical thinking, promoting the occurrence of the cognitive process and thus improving the performance of learners (Järvelä et al., 2016a, b; Roschelle & Teasley, 1995). Studies have identified cognition and emotion as crucial factors in collaborative learning and that emotion can lay the foundation for cognitive development (Järvelä & Hadwin, 2013; Kreijns et al., 2013; Phielix et al., 2011). Therefore, this present research pays attention to the interaction of cognition and emotion, which can be used as an exploration of the learning effect of learners.

Considering how regulated learning was embodied in social interaction, Molenaar and Chiu (2014) proposed the application of the three phases of regulated learning (forethought, performance and reflection) to collaborative situations. Sobocinski et al. (2017) integrated the concepts of cognition and emotion with the three phases of regulated learning to explore the time series of self-regulated phases and related interactions in low- and high-challenge collaborative learning sessions. Blau et al. (2020) conducted a qualitative analysis on reflective learning diaries which could showed learners' cognition to examine how cognitive, emotional and social aspects expressed in collaborative learning, and found that social-emotional statements could improve learners' self-regulation. Lobczowski (2020) explored how collaborative learning environments related to social-emotional regulation, and built a new model for emotion formation and regulation.

Discourse analysis is a framework and method for exploring the long-term relationship between language and social practice (Weissenrieder & Fairclough, 1997). Language is regarded as a social action in discourse analysis, which involves exploring, identifying, and comparing the ideas, thinking, and consensus of interlocutors (De Liddo et al., 2011). Basing on the language and social practice of learners, which are contained in discourse, researchers are able to find the cognition and emotion. However, the interaction of cognition and emotion as well as the regulation process of learners are invisible during the collaborative learning, which led to that researchers are unable to understand and analysis these process. Specifically, learners themselves could not recognize the existence of the process and teachers could not provide supports to helping learners achieve higher performance (Järvelä et al., 2020). Therefore, it is urgent that advanced technology and method are needed to visualize the process. According to the previous researches (Uzir et al., 2020; Wong et al., 2021), process mining can be a suitable method to explore the learning process through discourse. There are various process mining algorithms aiming to discover the process model from the event log. The steps of the process mining can be described as follows (Wang et al., 2012): (1) explores event traces from event logs; (2) analyzes event traces and obtains ordering relations between cases; (3) builds process model with ordering relations between cases.

This study used two algorithms in Process Mining, i.e. the inductive miner algorithm and heuristic mining algorithm. Heuristic mining algorithm discovers a heuristics net using a probabilistic approach and is good at dealing with noise which can run fast (Weijters & Van der Aalst, 2003). While Nuritha and Mahendrawathi (2017) compared heuristic and inductive miner algorithms for their different characteristics, properties, specializations, and performances in modeling business process, and used stuctural similarity measurement to get the result that inductive miner algorithm obtained better performance in dealing with noise. The current study applied inductive miner algorithm and heuristic mining algorithm to explore changes in learners' cognition and emotion over time as well as their interaction processes through discourse to understand their learning process in the context of blended collaborative learning.

2 Research review

2.1 Cognition and emotion in collaborative learning

The self-regulated process, which is influenced by learning goals and situational characteristics, is an adaptive regulation implemented by learners to promote personal development and refine learning strategies (Chen et al., 2019). During the collaborative learning, individual self-regulated was essential for promoting effective collaboration and improving academic achievement (Dindar et al., 2020). Self-regulated in collaborative learning, which refers to the regulation implemented by individual members of a group, can be applied to research on cognition, meta-cognition, motivation, emotions, and behavior (Lin & Li, 2019). Thus, this study applied selfregulated process to measure learners' cognition development in the process of collaborative learning.

Self-regulated learning theory focuses on the ideas of learners and emphasizes the interaction of motivation, emotion, and meta-cognitive and strategic behavior in success-ful learning, thereby translating the concept of learning into cognitive processes (Zimmerman & Schunk, 2011). Collaborative groups are considered as social systems that comprise multiple self-regulating individuals. Self-regulation involves personal adaptation, and responsibility for one's learning is an important aspect of collaboration. It is worthy of investigation that how learners regulate their learning processes and behavior patterns in the collaborative learning environment (Rogat & Linnenbrink-Garcia, 2011; Sobocinski et al., 2020). Some researchers had adopted temporal and sequential analysis of selfregulated learning (SRL) data to study how self-regulated occurred in collaborative learning environment (Molenaar & Chiu, 2014).

In SRL models, scholars considered active regulation by learners to be essential for the successful learning of the learners (Winne & Hadwin, 2008; Zimmerman, 2008). Regulatory activities include the acquisition of learning tasks and resources, the planning of learning processes, the regulation and control of learning steps, and the evaluation of learning results. Studies had confirmed that regulatory activities can promote and deepen collaborative learning (Chen et al., 2019; Lin & Li, 2019). As a periodic process, SRL comprises three phases: the forethought, performance, and reflection phases (Zimmerman, 2000).

During the forethought phase, learning motivation and self-regulated are stimulated and learners engage in task analysis (including goal setting and policy planning) and selfmotivation (including developing self-efficacy beliefs, outcome expectations, intrinsic interest, and goal orientation) to prepare for follow-up learning. Studies had explored the importance of the forethought phase in learning and found that compared with other students, students who set specific goals for learning tasks and apply previous knowledge adopt complex learning strategies in the performance phase. Learners' motivation in the forethought phase directly or indirectly affected learning effects and learning input through regulatory behavior (Gong et al., 2017; Malmberg et al., 2013).

The performance phase involves self-control and self-observation during the learning process. The self-control process helps students focus on tasks and apply the most effective strategies to achieve their goals. Self-observation is guided by the decisions made in the forethought phase and the interpretation of a specific situation to regulate learning behavior. Malmberg et al. (2013) noted that during the performance phase, students with high and low scores applied qualitatively different strategies when they believed that learning tasks were difficult.

After the performance phase, self-regulation enters the reflection phase. In the reflection phase, learners self-assess the information that they have collected and reflected on the results obtained by regulating behavior according to the goals set during the fore-thought phase. A learner's reflection on experience affects their subsequent forethought phases, which reflects the periodicity of self-regulated. For example, after obtaining negative feedback on performance, learners' self-efficacy beliefs and regulatory behavior decrease, which indicates that the reflection phase affects the forethought and performance phases of their next self-regulated cycle (Cleary et al., 2014).

Zheng et al. (2020) focused on learners' activities in the flipped classroom and found that there were contradictions in the collaborative learning, which could be resolved by self-regulated of cognition like co-regulation or shared regulation of cognition. Lim and Lim (2020) examined the relationship between achievement goal orientation and co-regulated which was expanded from self-regulated, and the results showed that mastering goal orientation played a predominant, positive role in collaborative learning environment. The study of Rahimi and Fathi (2021) aimed learners to co-construct and improve their writing performance and self-regulated through collaborative writing activities. All these researches showed that self-regulated which focused on cognition in collaborative learning important, while paid little attention to learners' emotions.

True emotions are exhibited in collaborative learning discourse, which is in agreement with the definition of social presence in community inquiry (CoI) theory. This theory indicates that learners exhibit social presence, which comprises the three dimensions of emotion, interaction, and group, online through social media (Rourke et al., 1999). Bai et al. (2016) considered the example of blended learning in a massive open online course and explored the relationships among teaching presence, cognitive presence, and social presence in CoI. They found that social presence can significantly predict cognitive presence and that emotion can promote cognition. Furthermore, cognitive presence in CoI emphasizes the behaviors and practices of learners (Swan et al., 2008). By contrast, the current study focused on time series in blended collaborative learning and used self-regulated phases that can reflect temporal information to detect learners' cognition.

2016). Picciano (2019) conducted a study on the social presence, interaction, and learning of students enrolled in online courses and found powerful correlations among these variables. They noted significant differences in the aforementioned variables among student groups with varying degrees of social presence. Lan et al. (2020) researched the relationships among the social presence, teaching presence, self-regulated and self-efficacy during the blended collaborative learning and found that social presence and teaching presence can predict and influence self-efficacy, while self-efficacy can predict and influence self-regulated. Xu et al. (2020) examined learners' behaviors to predict their productive participation identified by social presence indicators in online collaborative learning, showing that social presence indicators were related to meta-cognition and critical thinking. Thus, this study applied social presence to measure learners' emotions in the process of collaborative learning.

2.2 Process mining and interaction process

Process mining is a method used to explore event logs. The method can be used to obtain information, predict possible problems, identify potential countermeasures, and optimise process management. Process mining achieves this by identifying causes of events that would not be observable (Van der Aalst, 2016), which was well used in the field of medical, business, engineering and education. Educational process mining was developed and can be used to identify learning patterns, predict learning outcomes, optimise teaching assessments, inform teaching decisions, and improve educational management (Yan et al., 2020).

To investigate the role of self-regulated learning in acquiring technological pedagogical and content knowledge, Huang and Lajoie (2021) used process mining and analysed the log file data of teachers developing instruction plans in a computer environment. They discovered that excellent teachers were more likely to engage in self-regulated learning and more consistently sought to develop technological pedagogical and content knowledge. Cerezo et al. (2020) applied Inductive Miner to analyze learners' interaction traces on online platform and discovered their selfregulation models through time-series, which showed that although passing learners did not follow the instructors' suggestions exactly, they did follow the logic of a successful self-regulated learning process as opposed to failing ones.

Process mining is a useful method for analyzing data through time-series; however, the process of analyzing learner ideas is complex and may involve the analysis of overlapping events occurring within a short time (Lee & Seng, 2017). The code-and-count methods used in previous studies had masked small but crucial details that may indicate the understanding level of an individual or a group at a particular point (Chen et al., 2017). Moreover, the understanding of discourse depends on the context, and in-depth analysis must be conducted for truly understanding the intentions and motivation of learners. Process mining focuses on the relationship between the event frequency and the event sequence, which may be appropriate for analyzing time series.

The collaboration process is developed over time, and the progress of collaboration is crucial to learning success. Time series can describe students' learning activities and the practical processes of SRL (Johnson et al., 2011). The SRL process can be divided into two parts: the transitions between phases, such as the transition from the forethought phase to the reflection phase, and the sequential changing of characteristics over time, such as the student learning progress from the beginning to the end of a course (Järvelä et al., 2016a, b). Learners' input and the state of task completion change over time (Greene & Azevedo, 2010).

Ebrahim et al. (2020) had conducted a bibliometric analysis on research in timeseries classification, found that the research field had been broken down into three main categories as different frameworks of deep neural networks, different applications in remote sensing and in signal processing for time-series classification tasks. The third is related to the temporal analysis of education. But only a few studies have focused on the temporal aspects of regulated learning. These studies had identified the importance of the temporal characteristics of self-regulated in collaborative learning (Malmberg et al., 2017; Molenaar & Järvelä, 2014). SRL was commonly studied by computing the frequency of learning activities (Cleary et al., 2012), while the order and timing of actions were quite ignored (Winne, 2014).

Although emotion is the basis for the occurrence of cognition, few studies have temporally examined both these aspects in collaborative learning. Kapur (2011) believed that studying how the interaction between emotion and cognition changed in collaborative learning was crucial. The temporal changes in the interaction between cognition and emotion are relevant in collaborative learning situations because in these situations, group members must respond to the challenges emerging in the collaboration process and adjust the interaction between their cognition and emotion (Hadwin et al., 2011; Sobocinski et al., 2017).

The quality of the learning process depends on when the learner interacts with learning materials, peers, and teachers. Collaborative learning in online and blended learning environments allows the investigation of the aforementioned aspect. In addition, time-series studies can be conducted in the field of collaborative learning (Saqr & Nouri, 2020). Therefore, considering the coordinate between the time-series and process mining technology, the current study implemented blended learning with the support of WeChat to understand the interaction modes of cognition and emotion in learners' collaborative learning discourse on the basis of time-series data through the process mining. During the data collection process, interactions developed over time so that learning groups could achieve their common goals; therefore, interaction-related data from learning tasks were used to examine the regulatory process.

3 Material and methods

3.1 Participants

The participants (N = 30; 15 female and 15 male; M = 20.6; SD=0.49) of this study were undergraduate students enrolled in the aforementioned course. These students were divided into six groups of five people each. And we ranked the groups through

the collaborative learning performance. Specially, there were 10 females and 5 males in the high-scoring groups while 5 females and 10 males in the low-scoring groups. The groups were fixed throughout the collaborative learning course, and the course was conducted simultaneously in the same location for all the groups. WeChat was used to conduct and record the aforementioned course.

A 16-week course on information technology teaching contained the knowledge learners needed to learn, and involved six instructional design tasks and four classes of 45 min each. In each task, each group had to conduct instructional design on the basis of a certain information technology teaching method. A total of six classic teaching methods were used in the six tasks, which aiming at cultivating learners' abilities to apply the taught methods in instructional design. The students selected the entire course content and led the entire discourse, and they had to decide how to organize their work by themselves. Instructional design is a complex task because it requires students to perform activities such as browsing different textbooks, reviewing theories, selecting teaching and evaluation methods. Designing a lesson can be considered an ill-structured task that requires students to simulate the real scene, determine independently the methods and steps required to complete a task, and find the best solutions by applying different solutions. Thus, compared with well-structured tasks, ill-structured tasks offer students more challenges and opportunities to standardize and develop their learning abilities (Malmberg et al., 2014; Molenaar & Järvelä, 2014).

3.2 Research questions

A heuristic mining algorithm was used to calculate the dependency in each interaction between cognition and emotion (Sonnenberg & Bannert, 2015) for establishing timeseries interaction data related to collaborative learning. And an inductive miner algorithm was used to explore the differences between groups with high and low task scores over time. The research questions are as follows:

RQ1: How do cognition and emotion interact in blended collaborative learning? RQ2: What are the differences in and characteristics of the interaction processes of the high- and low-scoring groups?

3.3 Tools

3.3.1 Coding based on self-regulated phases and emotion

This study collected online chatting records from each group in each collaborative task. The coding process for the chat data of each learner involved two phases: determining the self-regulated phase and the emotion, including the cognitive-based interaction and social presence. Self-regulated phase and cognitive-based interaction were encoded according to the standard of Sobocinski et al. (2017), and social presence was coded by the social presence dimension in the CoI model (Rourke et al., 1999). Social presence captures different social relationships in a learning group. It comprises three dimensions, namely emotion, interaction,

and group, with a total of 12 sub-dimensions. The coding in this study was conducted by three researchers with backgrounds in pedagogy. Appendix presents the coding.

3.3.2 Analyzing the collaborative process by using inductive miner algorithm and heuristic mining algorithm

In this study, ProM 6.10 (Eindhoven Institute of Technology, Eindhoven, the Netherlands) was used for process mining.

Heuristic mining algorithm uses dependency to guide the creation of the interaction process and thus describe the level of association abstraction between events (Sonnenberg & Bannert, 2015). The degree of dependency is influenced by the event frequency and event sequence. The degree of dependency ranges from - 1 to 1 and is calculated as follows (Weijters et al., 2006):

$$F_{AB} = (f_{AB} - f_{BA}) / (f_{AB} + f_{BA} + 1)$$

where f_{AB} represents the number of times event A follows event B (the correct event sequence), f_{BA} represents the number of times event B follows event A (the incorrect event sequence), and F_{AB} represents the degree of dependency between events A and B. If a set of events contains 5 or 50 correct sequences and no incorrect sequences, the dependency between A and B is 5/6=0.83 or 50/51=0.98, respectively. This study summarized the collaborative learning interaction process for all the students in the six tasks through heuristic mining algorithm to show the overall learning process, and the detailed description is in 4.3.1.

The diagram of a collaborative interaction process built by heuristic mining algorithm represents event blocks, connection arcs, and the dependency, as shown in Fig. 1. A connection arc connects two sequential event blocks. An arrow (i.e., the end point of a connection arc) points to the next event, which can show the timeseries, and the dependency is indicated to suggest the degree of sequential association of the two event blocks. An event block indicates the frequency and type of an event. On the basis of the coded discourse data, the event block types considered in this study comprised self-regulated phases, cognition and emotion.

Inductive miner algorithm is rarely used in the field of education, however, when researchers need to reproduce the complete learning process and discover the behavior characteristics of extreme or small groups, this algorithm would have the high application value (Xu et al., 2022), which is suitable for the current study of 30 participants. Inductive miner algorithm mines the process tree of the event log with guaranteed fitness and contains unique behaviors (Leemans et al., 2018). There is also inductive visual miner which is a process exploration tool that shows an annotated interactive model for quick exploration of logs (Bolt et al., 2016). Some studies applied inductive miner to discover e-learning processes and students' self-regulated models that contribute to improving the instructional process (Bogarín et al., 2018; Cerezo et al., 2020). In order to better analysis the differences between the high- and low-scoring groups in collaborative learning, this

Dependency





Fig. 1 The example diagram of heuristic mining algorithm

study identified the interaction processes according to the time sequence of each task for these groups through inductive miner algorithm, and the detailed description is in 4.3.2 and 4.3.3.



Fig. 2 The example diagram of inductive miner algorithm

The model built by inductive miner algorithm represents boxes, arrows, frequency, and diamonds with a cross and begins with an initial node in green and ends with a final node in red. The numbers close to the initial node and the final node are the numbers of cases, such as the number of learners. The boxes are the events carried out by the learners where the number is the frequency. The arrows indicate the direction of the process, the number above the arrows is the frequency of the events, which can show the time-series of the events. The diamonds with a cross represent parallel paths, and the crossroad without any label on it represent forked paths. The example diagram of inductive miner algorithm is shown as Fig. 2.

3.4 Design framework

This study mainly involved three tasks: (1) collecting, sorting, and coding discourse data for collaborative learning; (2) applying a heuristic mining algorithm for overall process mining; and (3) applying a inductive miner algorithm for process mining of each task in different groups. Figure 3 displays the overall study design framework.

4 Data analysis and results

4.1 Consistency analysis

Time-series discourse data were collected in this study of each group in each task. Firstly, two encoders identified the self-regulated phase, cognition, and emotion in the discourse data. The Cronbach's alpha value of the coding was 0.967 greater than 0.9, which indicated that the coding consistency was satisfactory. Finally,



Fig. 3 Overall study design framework

the third encoder proofread and recoded ambiguous codes to increase the coding accuracy.

4.2 Discourse and interaction in collaboration learning

The six groups were ranked according to the collaborative learning performance of each group member. The first three groups were high-scoring groups, and the remaining three groups were low-scoring groups. The discourse data included information on the group, task, time, member, self-regulated phase, cognitivebased interaction, and social presence. Table 1 presents an example of coded discourse data, which was manually combed and encoded from WeChat chatting data.

The tasks were conducted successively on different days. In Table 1, the numbers in the member column represent the groups and code numbers of certain members; for example, "1–2" refers to the second member of the first group. The coding numbers of the members depended on the order in which they first appeared in the discourse. The coding methods adopted for the self-regulated phase, cognition, and emotion in Table 1 were consistent with those adopted for the self-regulated phases, cognitive-based interaction, and social presence in Appendix. Social presence comprises three dimensions, and each dimension would contain several sub-dimensions.

This study combined the self-regulated phase, cognitive-based interaction, and social presence to determine the interaction modes of cognition and emotion in blended collaborative learning. Table 2 lists the absolute frequency, relative

lable 1 Example of coded discourse data	Group	Task	Time	Member	self- regulated phase	Cognition	Emotion
	6	1	8:33:59	6–2	1	1	1
	6	1	8:34:09	6–3	1	1	1
	6	1	8:37:47	6–1	1	1	0
	6	1	8:39:09	6–4	1	1	1
	6	1	9:11:06	6–2	1	1	1
	6	1	9:11:29	6–4	1	1	1

frequency, minimum value, minimum value, mean value, and standard deviation (for the high- and low-scoring groups) for each interactive mode.

Table 2 reveals eight modes of interaction between cognition and emotion; however, no interaction was noted between the reflection phase and emotion. Compared with the low-scoring groups, the event frequencies of the forethought and reflection phases were significantly higher. By contrast, the event frequency of the performance phase was higher in the low-scoring groups. In general, the forethought and performance phases accounted for large proportions of the learning events for the high- and low-scoring groups. The reflection phase accounted for a small proportion of the learning events for these groups. In the forethought phase, the interaction between cognition and emotion was significantly stronger among the high-scoring groups than that among the low-scoring groups; however, in the performance phase, the frequency of cognition events was significantly higher for the low-scoring groups than for the high-scoring groups. Nevertheless, a t test exhibited no significant difference (p>0.05) in any event between the high- and low-scoring groups in the collaborative learning discourse.

4.3 Time-series data on the interaction process

4.3.1 Collaborative learning interaction process of all students in the six tasks

Through heuristic mining algorithm, Fig. 4 illustrates the interaction process of collaborative learning over the entire course in this study. The discourse data comprised information on 2256 discourse events for the six tasks and groups. The fitness value of the process diagram, which can range from negative infinity to 1, was 0.749 in this study. The closer this value is to 1, the higher is the fitness between the process diagram and the data. The process diagram includes event blocks, connection arcs, dependency, and central paths. The event blocks include the interaction modes of cognition and emotion and the event frequency. A connection arc connects two event blocks that occur successively and identifies the dependency between them. The central path is the event path with the highest dependency.

Multiple paths existed throughout the collaborative learning interaction process. The central path was "Start \rightarrow FORE | COG | EMO \rightarrow PERF | COG | EMO \rightarrow End," which is represented in Fig. 4. The input and output frequencies of the events were

Type of event	Low						High					
	Absolute frequency	Relative frequency	Min	Max	Mean	SD	Absolute frequency	Relative frequency	Min	Max	Mean	SD
Forethought phase	252	28.47%	4	35	14	8.534	535	39.02%	0	78	29.72	23.758
FOREICOG	27	3.05%	0	5	1.5	1.505	57	4.16%	0	11	3.17	3.258
FOREIEMO	6	1.02%	0	9	0.5	1.543	27	1.97%	0	19	1.5	4.475
FOREICOGIEMO	216	24.41%	ю	33	12	8.492	451	32.90%	0	63	25.06	19.833
Performance phase	618	69.83%	ю	74	34.33	22.927	764	55.73%	5	94	42.44	28.347
PERFICOG	238	26.89%	ю	32	13.22	8.922	218	15.90%	7	27	12.11	7.73
PERFIEMO	10	1.13%	0	5	0.56	1.338	18	1.31%	0	10	1	2.931
PERFICOGIEMO	370	41.81%	0	53	20.56	19.473	528	38.51%	1	75	29.33	24.071
Reflection phase	15	1.69%	0	5	0.83	1.295	72	5.25%	0	21	4	4.814
REFLICOG	1	0.11%	0	1	0.06	0.236	5	0.36%	0	2	0.28	0.575
REFLICOGIEMO	14	1.58%	0	5	0.78	1.263	67	4.89%	0	21	3.72	4.836
Total	885						1371					
COG cognition, EMC) emotion, FO	RE forethought phase,	PERF pe	rforman	ce phase, I	REFL reflect	tion phase					

groups
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Table 2



Fig. 4 Collaborative learning interaction process for all the students in the six tasks

2256 and 2144, respectively. Because of the sequence between some events was incompatible with the process diagram, the data for these events were eliminated; therefore, the output event frequency was less than the input event frequency. The presence of a loop inside an event block in the process diagram indicates that the relevant event occurred several times successively.

4.3.2 Collaborative learning interaction process of the high-scoring groups in the six tasks

The result of Cerezo et al. (2020) showed that the visualization of learning path in all learners cannot represented as a process but as a collection of actions, so it is necessary to analyze six tasks respectively to show a more structured learning process. The interaction processes for Tasks I–VI of the high-scoring groups are displayed in Fig. 5a-f.

For Task I, the fitness values of the process diagram as shown in Fig. 5a is 0.98, and the path with high-frequency extends from the interaction between cognition and emotion in the forethought phase to the end. Moreover, low-frequency parallel paths go through cognition, emotion or the interaction between cognition and emotion in the forethought phase, the performance phase and reflection phase.

For Task II, the fitness values of the process diagram as shown in Fig. 5b is 0.968, and the path with high-frequency is consistent with that in Task I. The events in the path with low-frequency are observed focusing on the interaction between cognition and emotion in the performance phase and the reflection phase.

For Task III, the fitness values of the process diagram as shown in Fig. 5c is 0.962, and the path with high-frequency is consistent with that in Task I and Task



Fig. 5 Interaction processes of the high-scoring groups in the six tasks

II. A low-frequency path is observed starting from the interaction between cognition and emotion in the reflection phase to cognition in the forethought phase developing to the performance phase and then to the interaction between cognition and emotion in the performance phase.

For Task IV, the fitness values of the process diagram as shown in Fig. 5d is 0.984, and the parallel events with high-frequency look like a collection of actions while focusing on the interaction between cognition and emotion in the forethought phase and performance phase. Moreover, a cycle of low-frequency is observed going through cognition in the forethought phase and reflection phase at the bottom of the Fig. 5d. The learning paths go through emotion in the performance phase to the end.

For Task V, the fitness values of the process diagram as shown in Fig. 5e is 0.87, and the path with high-frequency extends from the interaction between cognition and emotion in the forethought phase with other two parallel events to cognition in the reflection phase and then to the interaction between cognition and emotion in the performance phase.

For Task VI, the fitness values of the process diagram as shown in Fig. 5f is 0.962, and the path with high-frequency is observed starting from emotion to cognition in the performance phase with several parallel paths. Moreover, emotion and cognition in the forethought phase with low-frequency are observed at the beginning.

4.3.3 Collaborative learning interaction process of the low-scoring groups in the six tasks

Figure 6a-f illustrates the interaction processes for Tasks I–VI for the low-scoring groups.

For Task I, the fitness values of the process diagram as shown in Fig. 6a is 0.945, and the paths with high-frequency are observed between three parallel events, that is the interaction between cognition and emotion in the forethought phase, the interaction between cognition and emotion in the performance phase and cognition in the performance phase.

For Task II, the fitness values of the process diagram as shown in Fig. 6b is 0.974, and the path with high-frequency extends from the interaction between cognition and emotion in the forethought phase while turn back with a cognition event. Two parallel paths are both observed in the performance phase.

For Task III, the fitness values of the process diagram as shown in Fig. 6c is 0.803, and the path with high-frequency is consistent with that in Task II. Moreover, an interaction between cognition and emotion in the reflection phase with low-frequency in one parallel path is observed before the end.

For Task IV, the fitness values of the process diagram as shown in Fig. 6d is 0.885, and the path with high-frequency starts from the interaction between cognition and emotion in the forethought phase with parallel paths, and then extends to the interaction between cognition and emotion in the performance phase. Moreover, cognition in the forethought phase with low-frequency is observed at the beginning.

For Task V, the fitness values of the process diagram as shown in Fig. 6e is 0.87, and the paths with high-frequency are observed starting from the interaction between cognition and emotion in the forethought phase and then developing to the performance phase. The cognition in the forethought phase with low-frequency observed at the beginning is consistent with that in Task IV.



Fig. 6 Interaction processes of the low-scoring groups in the six tasks

For Task VI, the fitness values of the process diagram as shown in Fig. 6f is 0.93, and there are two parallel paths with almost the same frequency. One path extends from the interaction between cognition and emotion in the forethought phase to the end. The other path extends from cognition in the performance phase with cognition in the forethought phase at the beginning, events in the reflection phase during and the interaction between cognition and emotion in the performance phase before the end in low-frequency.

5 Discussion

The purposes of this study were to explore the interaction between cognition and emotion in the self-regulated phases in the blended collaborative learning and to examine the differences in this interaction between groups with high and low task scores. A comparison was conducted on the frequency of the collaborative learning events between the high- and low-scoring groups. This comparison indicated that the high-scoring groups exhibited more forethought and reflection phases than did the low-scoring groups. The interaction between cognition and emotion in the fore-thought phase enabled the students to apply complex learning strategies during the performance phase (Malmberg et al., 2013). Moreover, the reflection phase affected the learners' next forethought phase (Zimmerman, 2000). The tasks selected in this study were ill-structured and difficult tasks; thus, qualitative differences were noted between the strategies used by the high- and low-scoring groups during the performance phase (Malmberg et al., 2013).

The frequency of the interaction modes of emotion was significantly higher for the high-scoring students than for the low-scoring students, which is consistent with the discovery of Picciano (2019). Picciano divided students into groups with low-, middle- and high-level social presence and found that students with high-level social presence obtained higher task scores than did those with low-level social presence. No statistically significant differences were found in the collaborative learning discourse between the high- and low-scoring groups; however, differences were noted in the interaction processes of these groups. The aforementioned results indicate that no differences existed in the frequencies of the different self-regulated phases between the high- and low-scoring groups; however, the time series of these processes were different for these groups (Kapur, 2011).

The results indicate that the interaction processes of the high-scoring students had a higher number of cycles and branches than did those of the low-scoring students. Most of the interaction processes of the low-scoring students were linear. Thus, compared with the low-scoring groups, the high-scoring groups used more regulated learning strategies and regulation circuits (i.e., cycles in the interaction process that show the self-regulation of learners) in collaborative learning to achieve learning goals. However, the interaction sequence of the aforementioned groups mostly conformed to the periodicity of the self-regulated phase. This sequence was as follows: forethought, performance, and then reflection. Moreover, repeated cycles were observed from fore-thought to performance, which is consistent with the results of scholars such as Molenaar and Järvelä (2014) and Sobocinski et al. (2017). This finding shows that the cognition of learners is developing through the interaction in collaborative learning.

The events occurring in a group influence the construction of branches and cycles in the interaction processes. Therefore, in order to better analyzing the changes in the interaction processes of the high- and low-scoring groups with the progression of the task sequence, this study selected the interaction processes of one highscoring group and one low-scoring groups in the early, middle, and late phases of the course to represent the typical interaction modes. The interaction processes of the selected high-scoring group is displayed in Fig. 7. As illustrated in Fig. 7, the interaction process of the selected high-scoring group was linear in the early stage of the course; however, with the advancement of the course and an increase in task-related experience, the interaction process exhibited cycles of forethought and reflection, which indicates that learners adapt according to their learning progress. Moreover, an increase in the interaction between cognition and emotion was noted with the progression of the task sequence, which contradicts the conclusions of Sobocinski et al. (2017), who reported that cognitive activities were the main events in each learning phase. Therefore, the results of this study indicated that the interaction between cognition and emotion changed with learning progress.

Figure 8 displays the interaction processes of the selected low-scoring group. No difference was noted between the interaction modes of the selected high- and low-scoring groups at the beginning of the course. In the middle of the course, the low-scoring group still exhibited a linear interaction process; however, the number of interaction modes began to increase, and these modes adhered to the periodic order of the self-regulated phase. Similar to the high-scoring group, the low-scoring group exhibited a cyclic interaction process and the reflection phase in the late phase of the course; however, the reflection phase was less frequent for the low-scoring group than for the high-scoring group.

A comparison of the interaction processes of the selected high- and low-scoring groups indicated that the learning processes of the low-scoring group comprised more interaction modes but fewer cycles and branches than did those of the high-scoring group. The interaction modes of the high-scoring group were relatively fixed, and cycles appeared earlier in the interaction process of the high-scoring group than in that of the low-scoring group. The low-scoring group switched their interaction modes frequently and engaged in over-regulation, which led to increased cognitive load, which in turn worsened their learning outcomes. The high-scoring group worked through



Fig. 7 Interaction processes of the selected high-scoring group



Fig. 8 Interaction processes of the selected low-scoring group

several learning tasks to develop common cognition and find the main central path quickly. However, the low-scoring group found it difficult to develop common cognition in the learning process; therefore, they constantly explored possible new learning paths, which led to an increase in the number of interaction modes.

Finally, the results obtained for the proportions of the self-regulated phases indicated that for the high-scoring groups, the proportion of the performance phase gradually increased in the late phase of the course. This result was probably obtained because task difficulty decreases for learners as they receive training. Hadwin et al. (2011) believed that regulation occurs only when needed; therefore, as the difficulty of a task decreases, the team becomes increasingly focused on performing the task. For low awareness of task challenges or weak learning motivation, only limited changes occurred in the self-regulated phase of the low-scoring groups in the beginning and middle phases of the course.

The reflection phase exhibited the highest proportion among the phases in Task VI for the high- and low-scoring groups. In the late phase of a course, learners had accumulated certain learning experience and can better reflect and self-evaluate for a task. However, overall, the reflection phase had a relatively low proportion. The increasing trend of the reflection phase proportion is consistent with the findings of Ye and Pennisi (2022), who found that regulation and reflection were one of the most common SRL activities after finishing the learning tasks. This study explored the self-regulated phases of a learning task in which forethought- and performance-related processes had to be performed. The learners' regulation behaviors changed after the forethought or performance phases, which can be considered

a representation of reflection behavior. The data in this study were obtained from synchronous online discourse, and face-to-face oral discourse was ignored; thus, the proportion of the reflection phase was not high.

6 Conclusions

This study explored the interaction between cognition and emotion in blended collaborative learning. It investigated the learning process by using time-series data on synchronous online discourse and examined how cognition and emotion interact. This study also compared the characteristics of the interaction processes of groups with high and low task scores. This paper provides methods for understanding collaborative learning and presents suggestions for developing online and offline blended courses.

First, the interaction process of high-scoring groups exhibits three sequential self-regulated phases, and a relatively complete interaction between cognition and emotion occurs in each self-regulated phase. Moreover, the interaction mode of high-scoring groups is relatively fixed. By comparison, the interaction between cognition and emotion was insufficient for low-scoring groups. Moreover, the interaction mode of low-scoring groups was complex and variable. Therefore, teachers should play the role of guides in blended collaborative learning, pay attention to the interaction mode of learners, promote the association between learning content and students' social behaviors, help learners reduce their cognitive load, and improve learners' learning efficiency.

Second, compared with low-scoring groups, high-scoring groups exhibited more reflection phases and cycles in the interaction process and thus more frequent self-evaluation and regulation behavior for forethought and performance. Therefore, in the instructional design of a course, the feedback and evaluation setting throughout the course should be focused on. Moreover, teachers should focus on process evaluation and the combination of various evaluation methods, including self-evaluation and mutual evaluation.

Third, the frequency of emotion events unrelated with cognition was higher for high-scoring groups than for low-scoring groups; thus, when teaching, teachers should focus on the emotional attitude of learners. Irrelevant content, such as the expression of emotional behavior, can help relieve dullness in the learning process and thus lead to a positive influence on learners' learning outcomes.

This study has certain limitations. This study only examined the learning process and did not consider the preparation before the class and the summarization process after the class. The offline face-to-face discourse between learners was also not considered. The interaction process of cognitive and emotional is affected by cognition and motivation, and learners' learning ability also affect their enthusiasm for regulating learning (Gong et al., 2017; Malmberg et al., 2013), namely intrinsic differences among learners are unavoidable, and thus have an impact on research results.

Future research can explore the interaction between the cognition and emotion of learners during different periods in settings that are not limited to online discourse. Additional behavioral data can be collected for learners through various methods.

Moreover, in-depth analysis can be conducted to promote the creation of welldesigned courses in universities. In the teaching process, according to the difference between the low- and high-scoring groups, appropriate teaching intervention can be given to promote the interaction of cognitive and emotional in low-scoring groups or change their learning path, and the effectiveness of the teaching intervention can be tested by pre- and post-test.

Acknowledgments This work was supported the financial supports by National Science Foundation Youth Foundation of China "Research on Supporting Mechanism and Model Construction of Process Mining Technology for Teaching Decision-making in Online Sharing Regulation" Grant/Award Number: 62207026 and Higher Education "Fourteen Fifth" Teaching Reform Project in Zhejiang Province "Research and practice on the reform of evidence-based performance evaluation of AI technology" Grant/Award Number: jg20220101.

Author contributions Wei Xu and Ye-Feng Lou designed and carried out the research and conducted the data analysis and summary. Hang Chen and Zhi-Yi Shen conducted the research, and participated in the data analysis. All authors contributed to the article and approved the submitted version.

Funding This work was supported by the [National Science Foundation Youth Foundation] under [Grant number 62207026], and the [Higher Education "Fourteen Fifth" Teaching Reform Project in Zhejiang Province] under [Grant number jg20220101]

Data availability The database generated for this study is available upon request to the corresponding author.

Declarations

Ethics approval This study was carried out without ethics issue.

Consent to participate All participants gave their consent for participation.

Consent for publication All authors gave their consent for publication.

Competing interests The authors have no relevant financial or non-financial interests to disclose.

Conflict of interest The authors declare no conflicts of interest.

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