An artificial intelligence-driven learning analytics method to examine the collaborative problem-solving process from the complex adaptive systems perspective

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Abstract

Collaborative problem solving (CPS) enables student groups to complete learning tasks, construct knowledge, and solve problems. Previous research has argued the importance of examining the complexity of CPS, including its multimodality, dynamics, and synergy from the complex adaptive systems perspective. However, there is limited empirical research examining the adaptive and temporal characteristics of CPS, which may have led to an oversimplified representation of the real complexity of the CPS process. To expand our understanding of the nature of CPS in online interaction settings, the present research collected multimodal process and performance data (i.e., speech, computer screen recordings, concept map data) and proposed a three-layered analytical framework that integrated AI algorithms with learning analytics to analyze the regularity of groups' collaboration patterns. The results surfaced three types of collaborative patterns in groups, namely the behaviour-oriented collaborative pattern (Type 1) associated with medium-level performance, the communication-behaviour-synergistic collaborative pattern (Type 2) associated with high-level performance, and the communication-oriented collaborative pattern (Type 3) associated with low-level performance. This research further highlighted the multimodal, dynamic, and synergistic characteristics of groups' collaborative patterns to explain the emergence of an adaptive, self-organizing system during the CPS process. According to the empirical research results, theoretical, pedagogical, and analytical implications were discussed to guide the future research and practice of CPS.

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Introduction

Grounded in the social, cultural, and situated perspectives of learning (Vygotsky, 1978), collaborative problem solving (CPS), as one of the computer-supported collaborative learning (CSCL) modes, has been widely used in K-12 and higher education to foster active learning (Hmelo-Silver & DeSimone, 2013; Roschelle & Teasley, 1995; Stahl, 2009). CPS is a *multimodal*, *dynamic*, and *synergistic* phenomenon, where interactive, cognitive, regulative, behavioural, and socio-emotional aspects of collaboration take place synergistically, intertwine inseparably, and influence each other dynamically (Stahl & Hakkarainen, 2021; Vogler et al., 2017). These characteristics of CPS make it compatible with the complex adaptive systems theory, viewing education as a system containing various interdependent elements as well as dynamic and adaptive interactions between these elements (Byrne & Callaghan, 2014; Holland, 1996). Drawing upon the complex adaptive systems theory, therefore, traditional educational research methods (e.g., correlational analysis, regression, hierarchical linear modelling) may not be enough to holistically model and monitor the non-linear and dynamic characteristics of CPS (Amon et al., 2019; Vogler et al., 2017). Analytics of multimodal process data can be more beneficial for understanding the complexity of CPS (Janssen et al., 2013; Medina & Stahl, 2021; Wise et al., 2021). However, there is limited research examining the dynamic and temporal characteristics of CPS, which may have led to an oversimplified representation of the actual complexity of the CPS process. To fill this gap, the present research proposes a three-layered analytical framework that integrates AI algorithms with learning analytics methods to examine multimodal data collected during groups' CPS processes. This research reveals different types of collaborative patterns of group behaviour, and further examines the associated performance as well as the regularity of each type. Based on the empirical research results, theoretical, pedagogical, and analytical implications will be discussed to interpret CPS from a complex adaptive systems theory perspective.

Literature review

Collaborative problem solving and complex adaptive systems theory

Collaborative problem solving (CPS) requires student groups to solve complex and ill-structured problems without fixed answers in order to achieve the goal of collective knowledge co-construction (Barron, 2000; Roschelle & Teasley, 1995; Vrzakova et al., 2020). In the past decade, CPS has been widely conducted to promote students' active learning and meaning-making through various learning activities in order to enable students to connect and construct knowledge in a structured manner and create collective knowledge artifacts (Farrokhnia et al., 2019; Wang et al., 2017). CPS involves multiple levels of dynamic interactions between (1) individual students, (2) individual students and the student group(s), (3) individual students and the learning environment or a knowledge artifact, and (4) the student group(s) and the learning environment or knowledge artifact(s) (Stahl & Hakkarainen, 2021). This multilevel and multilayered nature of CPS indicates a certain level of complexity (Damşa, 2014; Stahl, 2013; Stahl & Hakkarainen, 2021).

Complex adaptive systems theory, originating from the field of biology, emphasizes that a system is a complex emergent entity that arises from the interactions between microscopic entities (Byrne & Callaghan, 2014; Holland, 1996; Lansing, 2003). When this concept is applied to the field of education, the teaching and learning processes can be viewed as a complex, self-organizing system, which emerges from interdependent interactions between individuals, groups, and teaching and learning components (Amon et al., 2019; Jacobson et al., 2016; Mitchell, 2009) (see Fig. 1). Furthermore, the CPS process is a complex phenomenon where a group of students constantly coordinates interactive, cognitive, regulative, behavioural, and social-emotional aspects through conversations and actions to adapt to the complex and dynamically changing collaborative context, eventually forming a self-organizing system. Therefore, the complex system perspective breaks the traditional educational research paradigms such as causal models or linear predictability and highlights the use of organic, nonlinear, and holistic approaches to understanding the nonlinear, dynamic evolution of CSCL (Amon et al., 2019; Holland, 1996).

The conception of complexity is not new to empirical research in the CSCL community. For example, Zuiker et al. (2016) combined complex adaptive systems theory as well as situated cognition theory to understand and explain collaborative learning as a system-level social activity. Vogler et al. (2017) used complex adaptive systems theory to explore how a message is shared by students in synchronous online discussions such that it triggered students' meaningful engagement in knowledge co-construction. Amon et al. (2019) investigated the system-level team dynamics in collaborative programming from a complex systems theory perspective in order to describe the dynamic, multimodal, and complex nature of collaboration. From the perspective of complex adaptive systems theory, these studies started to examine and illuminate how, in the dynamic process of CSCL, collab-
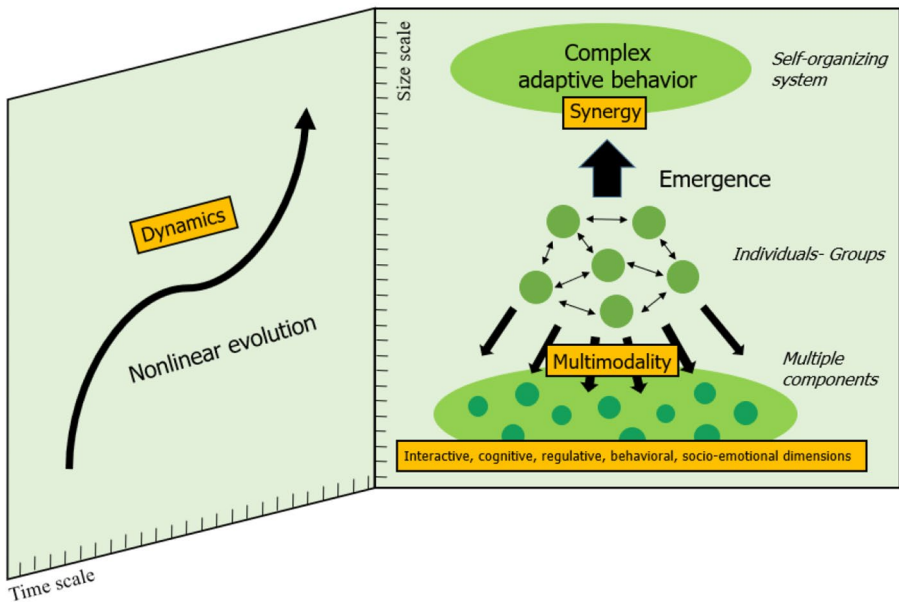

Fig. 1 The framework of complex adaptive systems theory. (adapted from Holland, 1996)

orative meaning-making processes are interwoven with the multimodality and dynamics of individuals, groups, learning environments, technologies, and resources during the CSCL process. Moreover, the CSCL community has paid attention to analyzing and understanding CSCL processes from the group or system perspectives, such as collaborative cognitive load, group-level metacognition, or group cognition (Dindar et al., 2020; Kuhn et al., 2020; Zheng et al., 2021). Overall, complex adaptive systems theory has the potential to contribute new perspectives to our understanding of educational phenomena, particularly the collaborative learning process, from a holistic, systematic, and non-linear perspective (Amon et al., 2019; Holland, 1996; Vogler et al., 2017).

The characteristics of CPS from the perspective of the complex adaptive systems theory

Grounded in the complex adaptive systems theory, group members in the CPS process form an adaptive, self-organizing system that has a multi-dimensional nature, synergistic relations, and a dynamic evolutionary character (Amon et al., 2019; Barron, 2000; Curşeu et al., 2020; Jacobson et al., 2016; Mitchell, 2009; Stahl & Hakkarainen, 2021). CPS's multimodal characteristics are reflected in the interactive, cognitive, regulative, behavioural, and socio-emotional aspects of the learning process (Fiore et al., 2010; Kwon et al., 2014; Malmberg et al., 2017; Zemel & Koschmann, 2013). On the interactive dimension, the multimodal interaction in CPS is built through students' discourse interaction, text interaction, and behaviour interaction, which together comprise the foundation of collaboration (Ouyang & Xu, 2022; Zemel & Koschmann, 2013). On the cognitive dimension, to solve ill-structured tasks, students need to share information and propose ideas to co-construct knowledge with group members (Barron, 2000; Ouyang & Chang, 2019; Vrzakova et al., 2020). On the regulative dimension, students need to understand the task, negotiate and plan the goal of the group, and monitor and reflect on their collaborative progress (Malmberg et al., 2017). On the behavioural dimension, students solve problems through online activities and coordinate their creation of knowledge artifacts as they regulate each other's behaviour (Fiore et al., 2010; Stahl, 2017). On the socio-emotional dimension, students need to engage in active listening, encourage participation, and contribute towards the creation of cohesive groups in order to foster active engagement, relaxation of tension, and the emergence of social motivation (Kwon et al., 2014; Rogat & Adams-Wiggins, 2015). More importantly, during the CPS process, this multiplicity of dimensions come together to form a complex, interdependent set of relationships that ultimately contribute to an adaptive, self-organizing system with multilevel and multilayered characteristics (Byrne & Callaghan, 2014; Hilpert & Marchand, 2018).

Furthermore, CPS is a dynamic process, where the relations between elements change over time, and ultimately affect the quality of collaboration (Holland, 1996; Hoppe et al., 2021; Koopmans & Stamovlasis, 2016; Saqr & López-Pernas, 2022). During the CPS process, students are required to adjust and coordinate interaction, behaviour, cognition, and emotional contributions to the evolving task context. As they do, they strive to achieve high-quality collaboration reflected in their knowledge construction process as well as the resulting knowledge artifacts (Amon et al., 2019; Barron, 2000; Wiltshire et al., 2019). For example, Amon et al. (2019) found that the regularity of coordinative patterns in students' speed of communication, body movement, and screen interaction over time in pair program-

ming can influence their collaborative learning outcomes. Saqr et al. (2021) applied various methods (e.g., process mining, sequence mining map, and temporal networks) to investigate the relational and temporal dynamics of students' self-regulated learning behaviours during online collaborative academic writing. Curşeu et al. (2020) proposed a multi-level dynamic model to examine how the variations of core self-evaluations, study engagement, group development, and relational conflict influences group identification in collaborative learning. In summary, there is emerging evidence that CPS is a *multimodal*, *dynamic*, and *synergistic* phenomenon, which might be better interpreted through the lens of the complex adaptive systems theory. However, studying CPS through this lens poses significant methodological challenges to traditional statistics, which are typically applied to homogenous, unimodal data sources that are frequently used in CSCL research.

The multimodal collaborative learning analytics of CPS

Collaborative learning analytics (CLA), an integration of CSCL and LA, is used to explain, diagnose, and promote collaborative learning processes (Wise et al., 2021). Due to the complexity of CPS, merely focusing on one dimension or perspective of collaboration may cause inconclusive and incomprehensible results. Therefore, CLA advocates the possibility to collect complex and multimodal data (e.g., behavioural, physiological, representational data) to develop comprehensive computational, algorithmic models of collaboration (Blikstein, 2013; Borge & Mercier, 2019; Mu et al., 2020; Ouyang et al., 2022; Sullivan & Keith, 2019). Echoing this trend, recent CSCL research has started utilizing multimodal learning analytics (MMLA), integrating multimodal data collection, learning analytics, and AI algorithm-enabled modelling to analyze and mine the complex, dynamic characteristics of CSCL processes (Gorman et al., 2020; Khan, 2017; Olsen et al., 2020; Sharma & Giannakos, 2020; Wiltshire et al., 2019). For example, Khan (2017) proposed a hierarchical computational approach to analyze multimodal data (including audio, video, and activity log files) and modelled the temporal dynamics of student behaviour patterns in collaboration. Wiltshire et al. (2019) used growth curve modelling to examine how students' multiscale movement coordination (e.g., speech, gestures, mouse and keyboard movement) changed across the duration of CPS. Gorman et al. (2020) used computational, quantitative models (including discrete recurrence, non-linear prediction algorithms, and average mutual information) to detect real-time changes in group communication reorganization patterns during collaborative training. The main premise of this emerging research stream is that, compared to traditional learning analytics, such as social network analysis (e.g., Ouyang, 2021) or content analysis (e.g., Jeong, 2013), integration of algorithm-enabled methods in learning analytics and educational data mining can better deal with complex, nonlinear information, as well as extract and represent multi-level and high-dimensional features of CSCL (de Carvalho & Zárate, 2020; Ouyang et al., 2023).

In this research, we present the results of our investigation of groups' collaborative patterns during CPS in an online, synchronous collaboration platform. Taking a complex adaptive systems theory perspective to interpret CPS, we collect and analyze the multimodal process and performance data of student groups, including verbal audios, computer screen recordings, and concept map data. Furthermore, we propose a three-layered analytical framework that integrated learning analytics and AI algorithm-driven methods to examine

the collaborative patterns and the regularity of those patterns. We aim to answer two main research questions:

1) *What types of collaborative patterns can be detected from students' multimodal data during their CPS activities in an online synchronous collaboration platform?*
2) *What are the performance differences of groups with different types of collaborative patterns observed during the CPS process in terms of their collaborative products?*

Methodology

Research context and participants

The research context was two graduate-level seminar courses, titled *Distance and Online Education* and *Online Learning Analytics* offered by the Educational Technology (ET) program at a top research-intensive university in China. The course was designed and facilitated by the same instructor (the first author). She designed a series of CPS activities for small groups (3 or 4 students per group) to work on (see Table 1). Groups were asked to complete one open-ended, ill-structured problem related to the course content in an online, synchronous collaboration platform named *huiyizhuo* (see Fig. 2). The current research dataset consisted of 24 datasets; each dataset included the group's audio recordings of verbal communication data (about 2,160 min in total), computer screen recordings of click stream data (about 2,160 min in total), text-based chatting, and the final product of concept map data. The instructor occasionally engaged in the CPS activities and her engagement was not the focus of this research; therefore, to maintain data consistency, the instructor data were all removed.

The instructional design of CPS activities followed the problem-based learning cycle (Hmelo-silver, 2004): students first analyzed the problem scenario, then identified the knowledge gap needed for solving the problem, and finally generated possible solutions through collaboratively building a concept map. Problems were all open-ended, ill-structured problems that did not have a fixed solution. For example, one CPS activity asked the groups to work as a teaching team to design online learning resources for high school classes. The online collaboration platform *Huiyizhuo* (https://www.huiyizhuo.com/) was used, which provides functions of text chatting, audio and video communication, concept map, note and comment, and resource sharing. In the CPS process, members first communicated through audio and text chatting, then shared resources and kept communications to share knowledge, and finally constructed a concept map to solve problems and propose solutions (see Fig. 2). The concept map was used as the main tool for the collaborative problem-solving process (Novak & Cañas, 2008).

The analytical framework, procedures, and methods

We proposed and used a three-layered analytic framework to examine the characteristics of collaborative patterns during CPS activities (see Fig. 3). AI algorithms were incorporated into that framework using multiple learning analytic approaches (e.g., quantitative content analysis, clickstream analysis, epistemic network analysis). In Layer 1 of data pre-process-

Table 1 Student information

Group	Participant	Gender	Age	Status	Course
Group A	A1	Female	32	Graduated student	*Distance and Online Education*
	A2	Male	41	Part-time Master student	
	A3	Male	25	Potential graduate student	
Group B	B1	Female	24	Full-time Master student	*Distance and Online Education*
	B2	Female	36	Full-time Ed.D. student	
	B3	Male	23	Full-time Master student	
Group C	C1	Female	24	Potential graduate student	*Distance and Online Education*
	C2	Male	31	Full-time Ph.D. student	
	C3	Female	27	Full-time Master student	
Group D	D1	Female	26	Full-time Ph.D. student	*Online Learning Analytics*
	D2	Female	23	Full-time Master student	
	D3	Female	23	Full-time Master student	
	D4	Female	23	Full-time Master student	

ing and analysis, we coded the *interactive, cognitive, behavioural, regulative*, and *socio-emotional* dimensions of CPS (see Table 2). In Layer 2, featuring a multichannel sequence analysis (MCSA), we examined the similarity of groups' CPS sequences in order to detect distinct clusters of collaboration patterns. In Layer 3, we used a multi-method approach (including statistical analysis, epistemic network analysis, and hidden Markov modeling) to further examine the regularities among different types of collaboration pattern clusters associated with particular student groups.

Layer 1: data pre-processing and analysis

The screen-capture data (with audio) was transcribed by two researchers in order to document temporal patterns in participants' verbal communications and online behaviours. The unit of analysis adopted for the transcription was the sentence (i.e., a full sentence spoken by
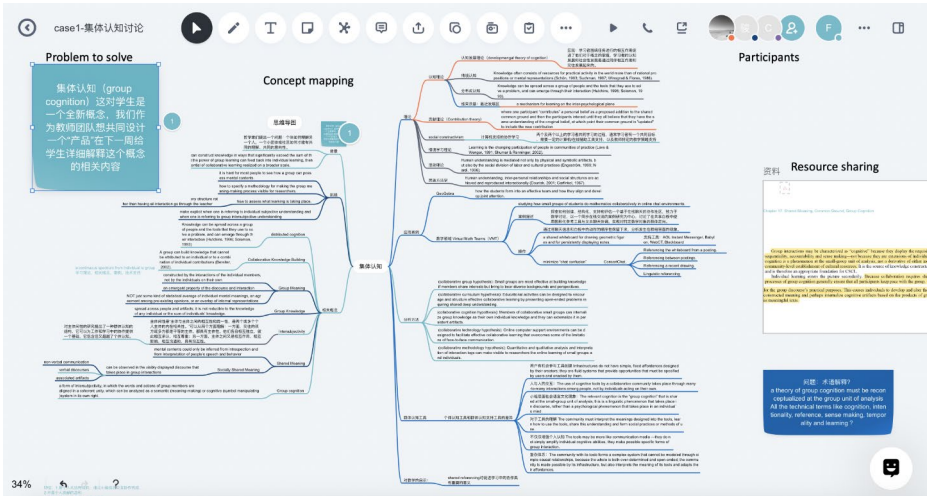
Fig. 2 A screenshot of a CPS activity on the *Huiyizhuo* platform
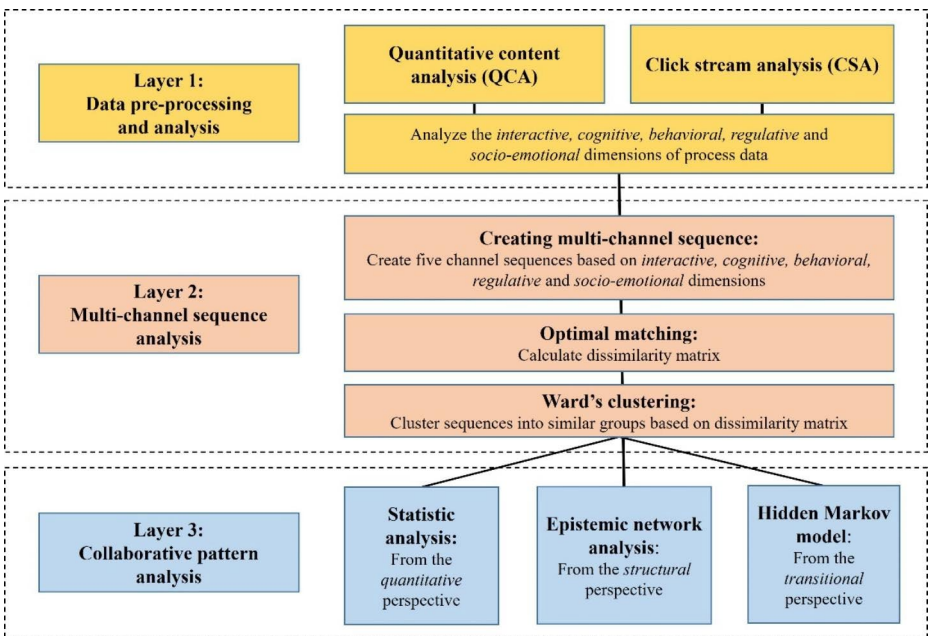

Fig. 3 The proposed three-layered analytical framework

a student) and the unit of analysis for the clickstream behaviour was a student's mouse click or mouse movement on the platform). After the transcription, 24 datasets included 11,477 units of verbal and behaviour data in total (Mean=478.21; SD=79.18). Drawing from the previous relevant literature, a coding framework was proposed to analyze the group's process data on the *interactive, cognitive, regulative, behavioural*, and *socio-emotional*

dimensions (see Table 2). It is worth mentioning that students may exhibit all these five dimensions as reflected through both verbal communications and online communication within their respective teams. There are two ways to address this multimodal nature of CPS. One way is assigning students' online behaviours to the cognitive and regulative dimensions (e.g., creating concepts or building on ideas on a concept map can be coded as the cognitive dimension, or moving the mouse to a concept map to observe can be coded as the regulative dimension). In this way, the original behavioural dimension is not recorded (see for instance in Ouyang & Xu, 2022). The second way is to maintain the behaviour as a separate dimension from the cognitive and regulative dimensions. Obviously, there is a tradeoff between these two strategies in terms of dealing with the overlaps of multiple dimensions during the CPS processes. After careful consideration, we decided to adopt the second strategy to retain and demonstrate the analysis results of students' behaviours. This decision is mainly driven by our theoretical positioning of CPS processes as complex and synergistic. The behavioural codes of online behaviours used are not just behaviour-oriented collaboration indicating students work on concept maps, but indirectly involve cognitive and regulative processes (see Table 2). With this strategy, more multimodal and complex characteristics can be captured, as compared to the first strategy.

Here we further explain the coding framework that includes the *interactive, cognitive, regulative, behavioural*, and *socio-emotional* dimensions of student groups' CPS processes (see Table 2). The *interactive* dimension recorded students' social interactions through peer communications and online behaviours of the concept map (Ouyang & Xu, 2022). The *cognitive* dimension analyzed students' knowledge contributions at the superficial, medium, and deep levels (Ouyang & Chang, 2019). The *regulative* dimension represented students' regulation of their collaborative processes, including task understanding, goal setting and planning, as well as monitoring and reflection (Malmberg et al., 2017). The behavioural dimension analyzed students' online behaviours, including resource management, concept mapping and observation. The *socio-emotional* dimension included active listening and respect, encouraging participation and inclusion, as well as fostering cohesion during the CPS processes (Rogat & Adams-Wiggins, 2015). It is important to note that although these theory-driven dimensions are indeed useful to label student interactions, they are proxies for tacit learning processes and certain levels of overlap between them are expected. For instance, the behavioural dimension, to a certain extent, might reflect the cognitive (i.e., KS, KM, KD) and regulative (i.e., MR) dimensions (see Table 2). Therefore, the behavioural dimension in this research not only refers to students' online behaviours, but may also reflect their cognitive and regulative efforts. During the coding process, if one unit included multiple dimensions (e.g., both interactive and socio-emotional dimensions in one unit of verbal communication), we assigned multiple codes in the corresponding unit. When the behavioural unit included the cognitive or regulative dimensions, we not only coded it at the behavioural dimension but also further examined the cognitive and regulative attributes of online behaviours (see 4.1 in the Results section).

Three raters completed the coding procedure. Rater 1 first coded 30% of the dataset based on the proposed coding scheme. Next, rater 2 coded the data again and then participated in multiple meetings with rater 1 to solve discrepancies. Krippendorff's (2004) alpha reliability was 0.802 among two raters at this phase. Finally, rater 1 completed the coding of the rest of the dataset, then rater 3 double-checked the coding results, and consulted with rater 1 to decide the final codes if there were any conflicts.

Table 2 The coding framework

Dimension	Code	Descriptions
Interactive (Ouyang & Xu, 2022)	Peer interaction through communications (Int-C)	A student interacted with peers through verbal communication (i.e., one student responded to others through audio) and texting (i.e., one student replied to others through text)
	Peer interaction through behaviours (Int-B)	A student interacted with peers by building on or modifying others' ideas on the concept map
Cognitive (Ouyang & Chang, 2019)	Superficial-level knowledge (KS)	A student shared existing information about the topic without further explanations or elaborations
	Medium-level knowledge (KM)	A student explained the details of the topic content without further elaborations
	Deep-level knowledge (KD)	A student explicitly elaborated the details of the topic content with detailed explanations, support of resources, statistics or personal experiences
Behavioural	Resource management (RM)	A student searched or shared resources on the platform or through the Internet
	Concept mapping (CM)	A student created, modified, or moved nodes created by himself/herself in the concept map; CM also indirectly reflected students' cognitive processes, including KS (the first-level node created on the concept maps), KM (arguments and explanations added to the second level of the concept map), and KD (examples added to the concept map to further support the arguments as the third level or above)
	Observation (OB)	A student moved the mouse over the platform to observe without any operations; OB also indirectly reflected students' regulative dimension (i.e., monitoring and reflection; MR)
Regulative (Malmberg et al., 2017)	Task understanding (TU)	A student read and explained the problems or questions of the tasks
	Goal setting and planning (GSP)	A student discussed the purpose of the task, divided the task into specific steps, and planned what to do next
	Monitoring and reflection (MR)	A student monitored the progress of tasks, evaluated the timeline for completing the task, and summarized what had been done and what needed to be done
Socio-emotional (Rogat & Adams-Wiggins, 2015)	Active listening and respect (ALR)	A student conveyed attention to other group members by responding to peers after careful listening
	Encouraging participation and inclusion (EPI)	A student encouraged the sustained involvement and contributions of group members
	Fostering cohesion (FC)	A student conveyed that the group functions as a team (rather than as individuals) by working together, referring to the group as "we"

Note. The coding framework clearly describes the codes we used as well as cites the previous literature from which the codes were derived

Layer 2: Multichannel sequence analysis

After data pre-processing and analysis, we applied multichannel sequence analysis (MCSA) to examine the similarity of groups' CPS activities in order to detect types of collaborative patterns. MCSA, as a sequence analysis method generated from the field of bioinformatics, is used to analyze multiple parallel trajectories (e.g., dimension, status) of time sequences simultaneously (Eisenberg-Guyot et al., 2020; Gauthier et al., 2010).

There were three steps for MCSA. In Step 1, the five-dimensional codes were transformed into five-channel sequences, and 24 five-channel sequences were created in total. Because

the CPS activities occurred in an authentic, natural collaborative context, the lengths of the 24 five-channel sequences were different. We decided not to truncate the sequences in order to standardize the length of sequences because we wanted to avoid information loss.

In Step 2, the optimal matching (OM) algorithm was used to calculate and align 24 five-channel CPS sequences in order to identify similar subsequences across them. In particular, the OM algorithm employed Levenshtein distance to measure the alignment between each pair of sequences in terms of edit distance (Abbott & Tsay, 2000). Thus, edit distances were computed in terms of the transformation steps (insertion, deletion, and substitution) that convert one sequence into another. The similarities between sequences were determined according to the generalized Hamming distance with user-defined transformation costs. The costs for insertion, deletion, and substitution were set to be the same (i.e., 1) in all dimensions to give them equal weight. No cost was set up for substituting missing states since we only detected similarities based on the observed trajectories. OM was implemented using R packages *TraMineR* (Gabadinho et al., 2011) and *seqHMM* (Helske & Helske, 2019).

In Step 3, Ward's clustering (WC) algorithm was used to cluster CPS activities into types with similar collaborative patterns. WC is a hierarchical bottom-up algorithm that computes similarities between sequences and clusters them into similarity-based groups (Murtagh & Legendre, 2014). WC was chosen because comparing to other clustering methods, it produces usable and relatively even-sized clusters. The choice of clusters was based on goodness-of-fit statistics, the dendrogram, and the interpretability of the clusters. WC was carried out through the R package *cluster* (Maechler et al., 2015).

Layer 3: Collaborative pattern analysis

In Layer 3, three analytic methods were used to reveal the quantitative, structural, and transitional characteristics of the collaborative patterns identified in step 2. First, from a quantitative perspective, statistical analysis (SA) was used to analyze the frequency of interactive, cognitive, regulative, behavioural and socio-emotional dimensions. Subsequently, a one-way analysis of variance (ANOVA) was conducted to test for significant differences between clusters.

Second, from a structural perspective, epistemic network analysis (ENA) was performed to reveal the inter-connections between patterns within and between the interactive, cognitive, regulative, behavioural, and socio-emotional dimensions. ENA is able to pinpoint and enumerate connections among elements in coded data and represent them within dynamic network models (Shaffer et al., 2016). An ENA Webkit (epistemicnetwork.org) was used to perform ENA analysis and its visualization (Marquart et al., 2018). However, the structure did not merely focus on the cognitive dimension, but in fact included all five dimensions.

Third, from a transitional perspective, a probabilistic approach referred to as hidden Markov modeling (HMM) was used to describe Markov Chains incorporating implicit parameters, detect latent processes with some number of hidden states, and find expected transition patterns between hidden states (Eddy, 1996). Compared to other algorithms for dynamic analysis (e.g., dynamic Bayesian networks), the advantage of the HMM is its ability to compress observed sequence data into simpler representations using hidden states (i.e., in our case the latent states are assumed to represent collaboration stages). HMMs capture the dynamic changes between states, which are implicit within the observed sequences and therefore unobserved (Eddy, 1996; Felsenstein & Churchill, 1996; Fine et al., 1998). The

R package *seqHMM* (Helske & Helske, 2019) was used to induce HMMs over clusters of sequences. In particular, a separate HMM was created and fitted for each type of collaboration pattern detected. The dataset included 15,750 codes for Type 1, 32,130 codes for Type 2, and 13,000 codes for Type 3. For each type, we set the desired number of states (between 2 and 9) for the target HMM, determined based on tuning for best fit. The expectation-maximization (EM) algorithm was used to estimate parameters through the process of fitting the HMM models. In order to reduce the risk of locally optimal solutions, the best fitting HMM was selected out of 100 runs with the R package *seqHMM*, each using a different random seed. The Bayesian information criterion (BIC) as the measure of fit used for choosing the optimal number of hidden states in each HMM, where lower values indicate better fit.

As a final performance measure, a validated assessment framework (Novak & Cañas, 2008) was utilized to evaluate each group's concept map data (see Table 3). The assessment included three dimensions, i.e., proposition, hierarchy, and example. Proposition refers to the basic themes and concepts associated with the topic (a meaningful proposition received 1 point); hierarchy refers to the hierarchical structure of a concept map based on connections between themes and concepts (an effective hierarchy received 5 points); and example refers to the use of an example to illustrate the corresponding themes and concepts (a valid example received 1 point). The final score of a concept map was the sum of scores across these three dimensions. Two raters evaluated each concept map individually and reached an interrater reliability of Krippendorff's (2004) alpha value of 0.912. After consulting with the first author, the final scores were confirmed.

Results

After Layer 1 of pre-processing and analysis, five dimensions (i.e., interactive, cognitive, regulative, behavioural, and socio-emotional) were coded for each CPS activity and transformed into 24 five-channel sequences. The optimal clustering results generated from Layer 2 revealed *three* types of collaborative patterns, consisting of 5, 14, and 5 CPS activities for Type 1, Type 2, and Type 3, respectively (see Figs. 4 and 5). As we can see from Figs. 4 and 24 datasets were generated from four groups (Groups A, B, C, and D), the distribution of four groups in the three types was relatively equal. Regarding the final performances of collaborative concept maps, although there was no statistical difference identified with the

| Dimension	Description	Scoring rules
Proposition	Did the concept map reflect basic themes and concepts? Was the relationship between topics correct and appropriate?	Each meaningful idea, concept, or argumentation received 1 point
Hierarchy	Did the concept map show a certain hierarchy? Was each subordinate concept more specific than the previous one?	Each effective hierarchical structure received 5 points
Example	Did examples in concept maps reflect their corresponding themes, concepts, or labels? Were examples used effectively and properly?	Each appropriate example or provided piece of evidence received 1 point

Table 3 Assessment of concept map. (adapted from Novak & Canas, 2008)
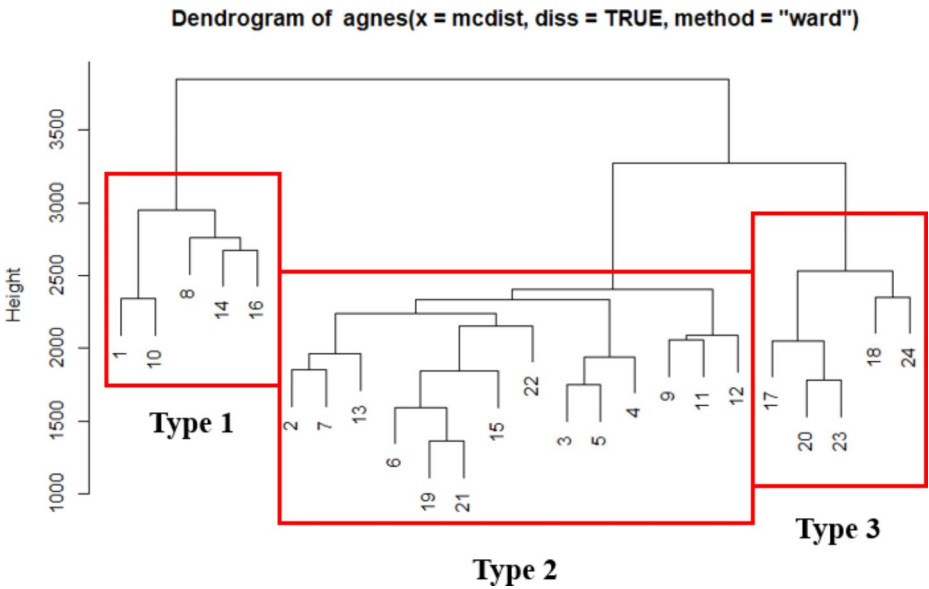
Fig. 4 Ward's clustering results for 24 CPS sequences

Note: In Type 1, no. 1 was Group D, no. 8 and 14 was Group B, no. 10 and 16 was Group A; In Type 2, no. 2, 3, 4, 5 were Group D, no. 6, 11 were Group B, no. 7, 9, 12, 15, 21 was Group C; no.13, 19, 22 was Group A; In Type 3, no. 17, 20, 23 was Group B, no. 18, 24 was Group C.

ANOVA tests, Type 2 had the highest score of concept maps (Mean=105.29, SD=33.64), followed by Type 1 (Mean=92.60, SD=23.67), and Type 3 (Mean=77.60, SD=28.18). In summary, Type 1 was associated with medium-level performance, Type 2 was associated with high-level performance, and Type 3 was associated with low-level performance.

From a quantitative perspective

ANOVA with the Bonferroni correction was conducted to test for significant differences between the three types on the five dimensions. Before ANOVAs, Levene tests were conducted; and the results confirmed the homogeneity of variance. Moreover, a series of post-hoc pairwise comparisons were conducted to further reveal significant differences between types (see Table 4). Considering that some data (e.g., TU, RM, OB, and EPI) were not normally distributed, a non-parametric test was conducted to cross-check the ANOVA results. The results showed that there were significant differences in the frequency of Int-B, KS, KM, TU, RM, CM, and OB ($p<.05$) with a Bonferroni correction using the Kruskal-Wallis test. Specifically, there were statistically significant differences between the three types along the *behavioural* dimension (RM, CM, OB). Regarding the main behaviours of concept mapping (i.e., CM), Type 1 ranked first among the three types, followed by Type 2 and Type 3. CM indirectly reflected students' *cognitive* engagement (i.e., KS, KM, and KD) when creating and editing nodes in the concept maps (Type 1: KS: Mean=9.40, KM: Mean=18.80, KD: Mean=61.40; Type 2: KS: Mean=7.64, KM: Mean=16.07, KD: Mean=51.14; Type 3: KS: Mean=4.00, KM: Mean=9.60, KD: Mean=17.20). In Type 3, more OB behaviors (Mean=146.8, SD=53.38) were detected than interactive behaviors (RM: Mean=20.6,
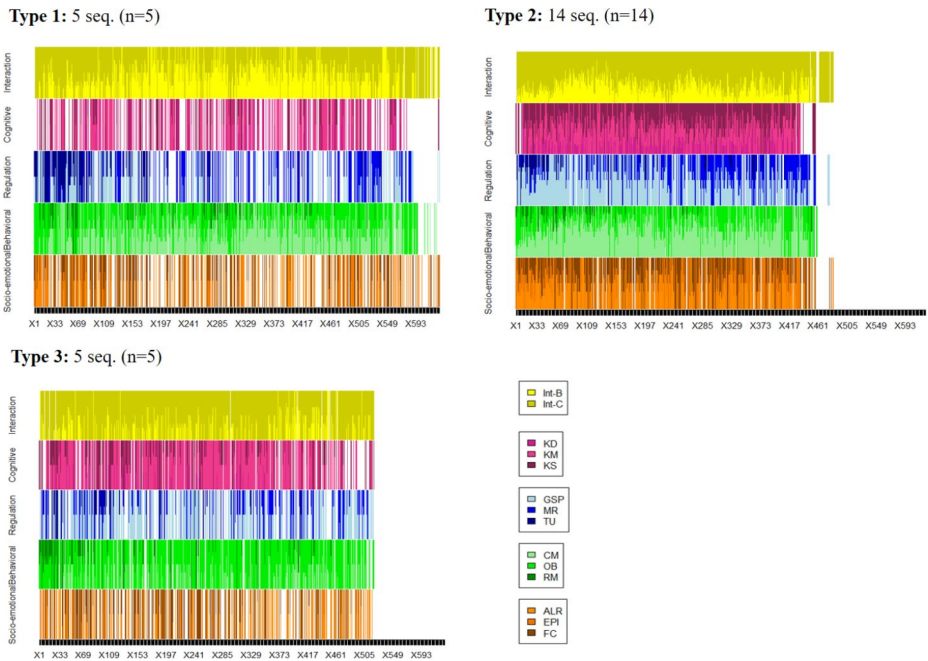
Fig. 5 Three types of collaborative patterns from optimal clustering results
Note: Each channel represents how the codes of a dimension change over time. Specifically, the first channel (yellow) represents the *interactive* dimension (Int-C and Int-B); the second channel (pink) represents the *cognitive* dimension (KS, KM, and KD); the third channel (blue) represents the *regulative* dimension (GSP, MR and TU); the fourth channel (green) represents the *behavioural* dimension (CM, OB, and RM); the fifth channel (orange) represents the *socio-emotional* dimension (ALR, EPI, and FC). The blank part indicates that no code was generated.

SD = 13.70; CM: Mean = 42.2, SD = 7.19). Moreover, OB, to some extent, also reflected students' monitoring of others' operations in the *regulative* dimension. Moreover, on the *interactive* dimension, statistical significance was found on Int-B, where Type 1 had the highest frequency, followed by Type 2 and Type 3; but no significant difference was found on Int-C, where all three types had a high level of Int-C. On the *cognitive* dimension, significant differences were found on KS (Type 2 > Type 1) and KM (Type 3 > Type 1, Type 3 > Type 2), except KD (all three types had a low level of KD). On the *regulative* dimension, significant differences were found on TU (Type 1 > Type 2, Type 1 > Type 3), while no significant difference was found on GSP and MR. In addition, no significant difference was found in the *socio-emotional* dimension, possibly due to sparsity. We thus concluded that in general there were different collaborative patterns among the three types.

From a structural perspective

From a structural perspective, three types were characterized by a representation indicating the connection values and the locations of the centroid of the ENA plots (see Fig. 6). First, representations of the regularities represented by each type were constructed using three pairs of connected codes (connection values > 0.40). They were Int-C – KM, Int-C – OB,

Table 4 Results of frequencies and one-way ANOVAs of the three types

Code	Type 1 (n=5) Mean (SD)	Type 2 (n=14) Mean (SD)	Type 3 (n=5) Mean (SD)	ANOVA F	p	Post-hoc pairwise comparison
Interactive						
Int-C	215.20 (103.38)	213.93 (67.91)	239.60 (60.72)	0.23	>0.10	
Int-B	176.20 (19.83)	105.43 (42.95)	52.40 (20.98)	14.91	<0.001***	Type 1>Type 2>Type 3
Cognitive						
KS	23.60 (17.95)	56.36 (21.68)	39.60 (13.72)	5.43	<0.05 **	Type 2>Type 1
KM	54.20 (32.51)	59.14 (27.25)	105.00 (29.73)	5.36	<0.05 **	Type 3>Type 1, Type 3>Type 2
KD	17.40 (12.74)	20.64 (16.09)	11.60 (5.41)	0.77	>0.10	
Regulative						
TU	28.80 (12.76)	7.36 (6.34)	11.00 (6.36)	13.44	<0.001***	Type 1>Type 2, Type 1>Type 3
GSP	49.60 (21.95)	46.71 (23.88)	70.40 (27.32)	1.80	>0.10	
MR	39.80 (18.90)	24.50 (17.30)	31.40 (10.43)	1.63	>0.10	
Behavioural						
RM	20.20 (17.66)	6.86 (7.77)	20.60 (13.70)	4.04	<0.05 **	Type 1>Type 2, Type 3>Type 2
CM	160.80 (37.31)	97.36 (34.18)	42.20 (7.19)	17.67	<0.001***	Type 1>Type 2>Type 3
OB	154.20 (75.62)	54.29 (26.77)	146.80 (58.38)	12.41	<0.001***	Type 1>Type 2, Type 3>Type 2
Socio-emotional						
ALR	35.00 (11.64)	36.43 (13.30)	35.00 (13.51)	0.04	>0.10	
EPI	24.80 (24.66)	19.64 (15.55)	10.80 (5.45)	0.94	>0.10	
FC	36.40 (23.42)	28.29 (20.41)	32.40 (18.80)	0.30	>0.10	

Note. $* p<.10$, $** p<.05$, $*** p<.001$

For simplicity, although the cognitive and regulative dimensions were reflected in patterns of online behaviours, the details of the results related to cognitive (KS, KM, and KD) as well as regulative (MR) dimensions were only described in the text and not shown in Table 4.

and Int-C – Int-B. The *socio-emotional* dimension was weakly associated with other codes (connection values < 0.40) in the representations associated with each of the three types.
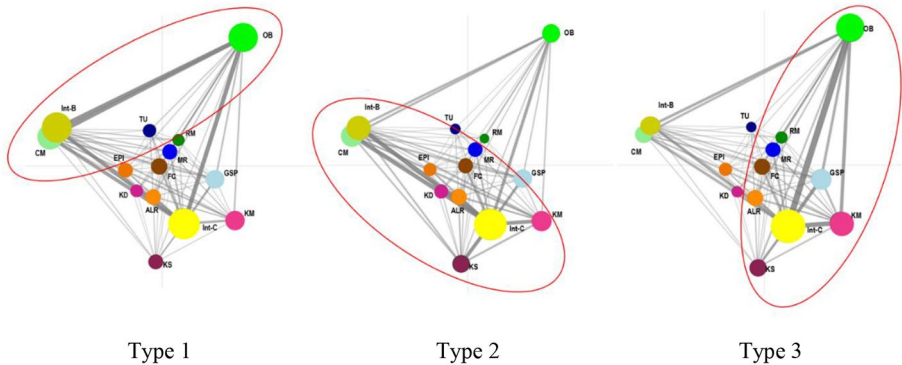

Type 1   Type 2   Type 3

Fig. 6 The epistemic network analysis of the three types of collaboration patterns
The colours of the codes are not automatically generated through ENA Webkit, but set manually by researchers according to the code colour

Different characteristics were identified among the three types of collaboration pattern clusters, reflected by the respective locations of the centroid in each epistemic network (shown as red circles in Fig. 6). For Type 1, the centroid of the epistemic network was located at the upper left corner, focusing on the behaviour-related codes (including OB, CM, and Int-B). The connection between Int-B and OB was 0.74; the connection between Int-B and CM was 0.72; and the connection between OB and CM was 0.69. For Type 2, the centroid was located at the bottom of the epistemic network, focusing on the behaviour and communication-related codes (including CM, KM, KS, Int-B, and Int-C). The connection between Int-B and Int-C was 0.71; the connection between Int-C and CM was 0.67; the connection between Int-C and KM was 0.62; the connection between Int-C and KS was 0.61; and the connection between Int-B and CM was 0.60. For Type 3, the centroid of the epistemic network was located on the right side, mainly focusing on communication-related codes (including KM, GSP, and Int-C). The connection between Int-C and OB was 0.90; the connection between Int-C and KM was 0.73; and the connection between Int-C and GSP was 0.59. In summary, Type 1 concentrated on the *behaviour-related* codes; Type 2 focused on both *communication-related* and *behaviour-related* codes, and Type 3 concentrated on the *communication-related* codes.

From a transitional perspective

From a transitional perspective, similar characteristics among the three types of collaboration pattern clusters were observed in the HMM results. Specifically, a 5-state HMM of Type 1, a 7-state HMM of Type 2, and a 5-state HMM of Type 3 were selected based on fit, where the lowest values for BIC are preferred (see Table 5; Fig. 7, and Fig. 8). Among the HMM results, a regular transition pattern was observed such that *communication* (State 1 in Type 1, 2, 3), moved to *behaviour* (State 2 in Type 1, 3 and State 2, 4 in Type 2), and finally returned to *communication* (State 3, 4 in Type 1, 3 and State 5, 6 in Type 2) (see Table 5; Fig. 7).

	Hidden state	Type 1	Type 2	Type 3
Table 5 Descriptions of hidden states in HMMs of the three types	1	Students communicated with each other	Students interacted with each other through communication and behaviours	Students communicated with each other and sometimes observed
	2	Students operated the concept map together and sometimes observed	Students operated the concept map together while sometimes observing others or communicating with each other	Students observed others, sometimes communicated with each other, operated the concept map, or managed resources
	3	Students constructed knowledge through peer communication	Students communicated with each other to set goals and plans	Students constructed knowledge through peer communications
	4	Students mainly operated the concept map and sometimes communicated with each other	Students operated and modified the concept map and sometimes observed others	Students communicated with each other and sometimes observed
	5	Collaboration ended	Students communicated with each other	Collaboration ended
	6		Students interacted with each other through communication and behaviours	
	7		Collaboration ended	

Note HMMs are shown as directed graphs, where the pies represent hidden states and the slices show the probabilities of observed states within each hidden state. Observed states are shown as labels, which represent the codes observed at the same time from five dimensions (probabilities > 0.05 is shown). The arrows indicate transition probabilities between the hidden states; the thicker the arrow, the higher the probability. No code is detected when no code is generated across all five dimensions.

A regularity was detected in the transition patterns such that where Type 1 was characterized as a *behaviour-oriented transition*, Type 2 was characterized as a *communication-behaviour-synergistic transition*, and Type 3 was characterized as *a communication-oriented transition*. In Type 1, groups were more likely to transition from other states to the behaviour-related states (State 2, 4) (see Fig. 7). Additionally, states related to peer communications (State 1, 3) were short and infrequent, while states of peer behaviours (State 2, 4) were long and frequent (see Fig. 8). In Type 2, students had a high probability of transitioning to State 4 and State 6, which included both communication-related and behaviour-related codes. Except for State 3 and State 4, each state in Type 2 shared a balance of time and frequency across the CPS processes. In Type 3, groups had the highest probability of tran-
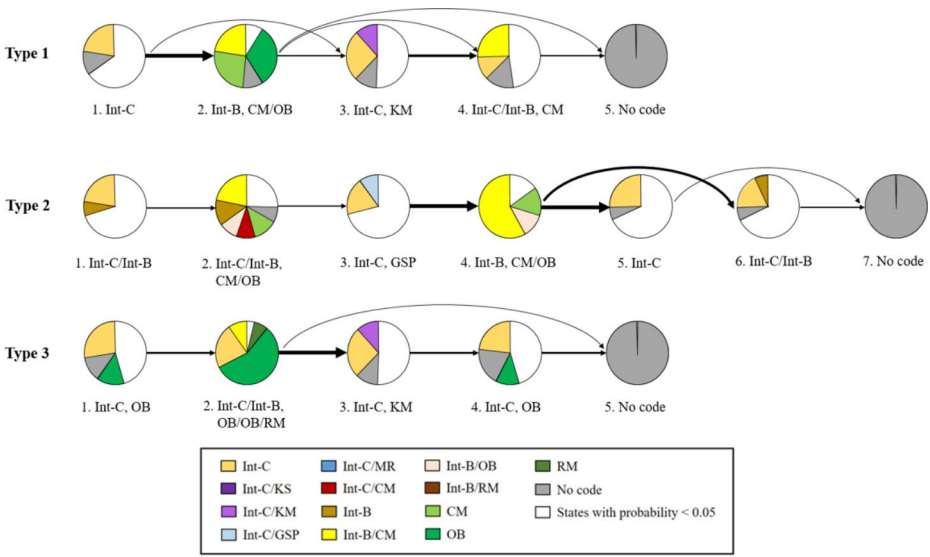
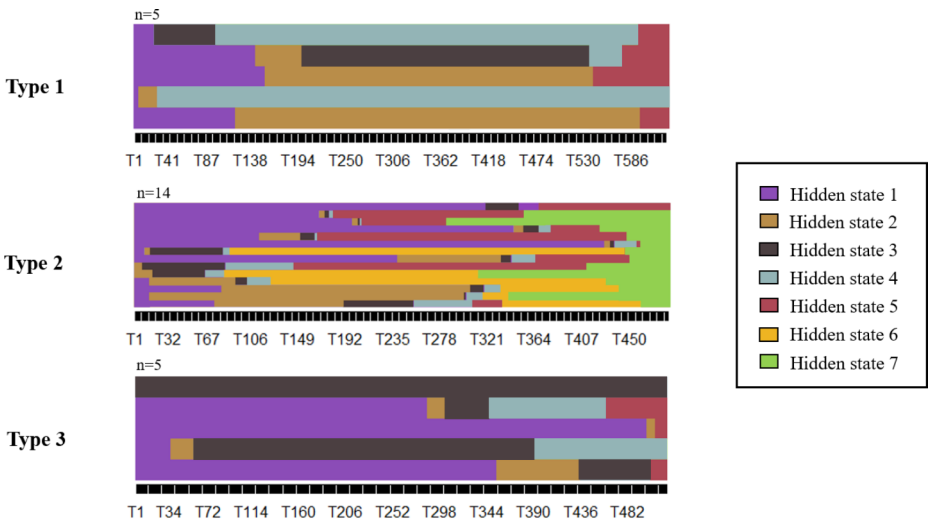**Fig. 7** HMM graphs of the transitional structures among the three types

Fig. 8 Most probable HMM paths among the three types

sitioning to a communication-related state (State 3). States dominated by peer communications (State 1, 3) were long and frequent, while states dominated by peer behaviours (State 2, 4) were short and infrequent.

Discussion

Addressing research questions

Due to the complexity of CPS (Amon et al., 2019; Jacobson et al., 2016; Stahl & Hakkarainen, 2021), unimodal data and traditional statistics may be limited for holistically modelling it (Ouyang et al., 2022). This research collects multimodal data, including speech, screen-capture recordings, and concept map data, and proposes a three-layered analytical framework integrating learning analytics and AI algorithm-driven methods to investigate the collaboration patterns of groups working through an online collaboration platform. Compared to previous studies, this approach proposes a multilayered approach to better understand the complex nature of CPS from an organic, nonlinear, and holistic perspective that is aligned with the complex adaptive systems theory (Vogler et al., 2017; Zuiker et al., 2016). To answer the research questions, three types of collaborative patterns were detected with different levels of the final concept map performance: Type 1 was characterized as a behaviour-oriented collaborative pattern and associated with medium-level performance, Type 2 was characterized as a communication-behaviour-synergistic collaborative pattern and associated with high-level performance, and Type 3 was characterized as a communication-oriented collaborative pattern and associated with a low-level performance. More importantly, the attributes of the three types were together demonstrated through the quantitative frequency, structural, and transitional aspects as the results showed. Regarding the behaviour of concept mapping (i.e., CM), Type 1 ranked first among the three types, followed by Type 2, and Type 3. Since the complexity of CPS, the cognitive dimension was also reflected through students' online behaviours as knowledge sharing and construction during the concept mapping process, which partially explained the relations between the groups' behaviours and final performances. For example, Type 3 had the lowest level of cognitive engagement (KS, KM, and KD) through online behaviours, which also resulted in the lowest score of the final performance among the three types. The ENA and HMM results also indicated different characteristics of the three types. For example, Type 2 shared strong connections between communication-related and behaviour-related codes with a communication-behaviour-synergistic transition; Type 1 generated strong connections only within the behaviour-related codes with a behaviour-oriented transition; Type 3 generated strong connections only within the communication-related codes with a communication-oriented transition. Overall, this research revealed three types of collaborative patterns in CPS as well as their characteristics to further verify the multimodality, dynamics, and synergy of the CPS process.

Theoretical implications: the complexity of collaboration

The complexity theory, as an emerging paradigm in educational research (Morrison, 2002), looks at and examines the educational system in ways that break with the simple cause-and-effect models, linear modelling, and regression and replaces them with organic, non-linear, and holistic approaches (Cohen et al., 2013). The recently published international handbook of computer-supported collaborative learning calls for the application of AI algorithm-based models to model complex systems and learner self-organization for collaboration at various scales (Cress et al., 2021). From the perspective of complex adaptive systems theory, CPS

is a complex phenomenon, in which group members interact with each other, the learning environment, or the knowledge artifacts adaptively to form a group-level, collaborative pattern and collective intelligence (Jacobson et al., 2016). This research provides a new method to explain the emergence of a self-organizing system during the CPS process by integrating AI algorithms with learning analytics and various modalities of data to analyze *multimodal*, *dynamic*, and *synergistic* characteristics of collaboration.

First, the results demonstrated the *multimodal* characteristics of collaborative learning, reflected by the interactive, cognitive, regulative, behavioural, and socio-emotional dimensions, which formed the foundation for the emergence of an adaptive, self-organizing system as observed within Markov models' distinctive state-transition patterns associated with different types. Consistent with previous studies (e.g., Ouyang & Chang, 2019; Park et al., 2015), we found that groups' peer interactions were primarily reflected in students' verbal communications, and the cognitive and regulative dimensions were closely related to peer interactions via verbal discourses. In other words, active peer communications formed a foundation for deep-level knowledge construction and group regulation (Zemel & Koschmann, 2013). On the behavioural dimension, collaborative patterns with high and medium performance had more active behaviours (i.e., concept mapping, and resource management), while low performing patterns were associated with more passive behaviours (i.e., observation). In addition, the cognitive dimension was also reflected in students' online behaviours as knowledge construction in concept mapping, which might partially explain the relations between groups' behaviours and final performance. For example, our results showed that Type 3 had the lowest level of knowledge construction through students' online behaviours, which also resulted in the lowest collaborative performance among the three types. Moreover, more deep-level knowledge was generated through concept mapping behaviours than verbal communications. Therefore, in the multimodal CPS process, we are able to infer that online behaviour might play a critical role in transforming students' superficial-level and medium-level knowledge in verbal discourse into a deep-level knowledge co-construction (Ouyang & Xu, 2022). However, inconsistent with previous studies that highlighted the role of social emotions (e.g., Kwon et al., 2014; Rogat & Adams-Wiggins, 2015), no significant difference was found between collaborative patterns on the social-emotional dimension. Apart from that, the socio-emotional dimension was weakly-connected with other dimensions. One of the potential reasons is that there may be a cultural aversion to students expressing their social emotions during collaboration (Zhang, 2007, 2013). These results indicate the complex connections between multiple dimensions emerging into the multimodality of CPS, which in turn influences the collaborative outcomes of group interactions.

Second, the *dynamic* characteristics uncovered how an adaptive, self-organizing systems emerged within groups during the CPS processes as observed in Markov models' distinct states for each type of pattern. When confronted with a new problem, groups tended to discuss it together to understand the task and set a specific goal (i.e., communication state). Initial verbal communications in this stage helped groups of students adapt to the social-collaborative environment and become familiar with their group members, which is beneficial to transitioning students into active collaborators (Kwon et al., 2014). However, less cognitive engagement was found in the initial communication stage. Since meaningful knowledge construction belongs to a relatively higher level in CPS, it might require more complex factors (Roschelle & Teasley, 1995). It might also appear based on enough peer interaction and the feeling of safety and collaboration (Schindler & Bakker, 2020; Zemel &

Koschmann, 2013). After that, some students started operating concept maps or managing resources, and others kept observing (i.e., behaviour state). In this stage, students' cognitive engagement and metacognitive regulation are mainly reflected through their online behaviours and sometimes presented by means of verbal communication. When new difficulties or bottlenecks appeared, students would suspend their work in order to make time to discuss it again and reflect on how to solve the problems (i.e., communication state). This research demonstrated how groups evolved through the developmental stages (i.e., from communication to behaviour and back to communication) to adapt to the ongoing changes in collaboration demands and finally form a self-organizing system with relatively stable states and their associated transition probabilities.

Third, as one of the keys to succeed in forming an adaptive, self-organizing system during collaboration, the *synergistic* characteristics were embodied in groups' coordination between communication and behaviour. Similar to previous studies (e.g., Amon et al., 2019; Ramenzoni et al., 2012; Wiltshire et al., 2019), these findings indicated that high-performing groups (i.e., Type 2) gave rise to synergistic collaboration across verbal discourses and online behaviours in order to adapt to the shifting task demands. However, considering the external factors (e.g., task difficulty, group configuration, social learning context), it is challenging for all groups to collaborate synergistically and to achieve a high quality of collaboration. For example, the medium-performing groups (i.e., Type 1) were more likely to involve online behaviours (e.g., concept mapping) to drive CPS activities, while the low-performing groups (i.e., Type 3) were more likely to conduct CPS activities through verbal discourses. Furthermore, the ENA connection values were relatively stronger in Type 1 and Type 3 than in Type 2, which to some extent verified the difficulty of achieving a high-quality synergy between communication and behaviour in the CPS processes. Overall, this research highlights the complex characteristics of collaborative learning, which further argue for multi-dimensional, multi-level, and multi-perspective analytical approaches to collaborative learning research (Cohen et al., 2013; Jacobson et al., 2016; Morrison, 2002). This research builds a bridge between the complex adaptive systems theory and analytics of collaborative learning to guide future empirical studies in the CSCL field that would take similar approaches to the investigation of students' group interactions.

Analytical implications

Since collaborative learning is a complex, adaptive process, this research extends investigations on using AI-driven learning analytics to understand *multimodal*, *dynamic*, and *synergistic* characteristics of groups' collaborative patterns during a complex collaborative task. On the one hand, multimodal data collection and analysis are suggested for the investigation of complex educational phenomena and problems (Cukurova et al., 2020; Michail Giannakos, Roberto Martinez-Maldonado; Stahl & Hakkarainen, 2021; Vogler et al., 2017). Recent research has used multimodal data (e.g., speech rate, gesture, body movement, eye movement) to examine the collaboration patterns and characteristics in CSCL, which can complement analysis results from traditional discourse, online content, and product data (Amon et al., 2019; Blikstein, 2013; Mu et al., 2020). More importantly, due to the complexity of CPS, the multiple dimensions (e.g., interactive, cognitive, regulative) might be reflected through communication and the behaviour of collaboration. For example, the behaviours in this research also indirectly reflected the cognitive engagement and metacognitive regula-

tion of the groups of students during the CPS processes. On the other hand, this research verified that the AI algorithm-enabled learning analytics and data mining approach can help to reveal complex characteristics of CPS from quantitative, structural, and transitional perspectives. Compared to traditional learning analytics methods, the integration of learning analytics approaches and algorithm-enabled methods can better process multimodal and nonlinear data in order to extract and represent the complex and dynamic structure of CSCL (de Carvalho & Zárate, 2020). For example, HMMs have the potential to capture the stable, distinct states of CPS as well as dynamic movements between and within them, which has the particular ability to reveal the adaptive, self-organizing character of collaborative learning. Furthermore, advanced AI algorithms (e.g., multidimensional recurrence quantification analysis, natural language processing, genetic programming) have been applied in CSCL to analyze and reveal the complexity and dynamics of collaboration (Amon et al., 2019; de Carvalho & Zárate, 2020; Hoppe et al., 2021; Sullivan & Keith, 2019). Future work can further integrate these advanced AI algorithms with learning analytics and data mining to reveal the multilevel, multidimensional characteristics of CSCL. There is a call for the application of technological advances (such as machine learning) to foster real-time feedback and assessment of group work, identify collaboration patterns to effectively guide productive collaboration, and accurately predict collaborative outcomes (Amon et al., 2019; Eloy et al., 2019; Xu & Ouyang, 2022).

Pedagogical implications

CPS is a complex process that is unlikely to follow a particular model of linear sequences of actions. Therefore, during the CPS process, instructors should provide dynamic scaffolding as well as adaptive support to promote students' collaboration. First, instructors can provide different scaffolding to enhance groups' collaboration quality based on the multimodal characteristics of CPS. For example, the foundational role of active communications was reinforced by the research results, therefore, instructors are able to regulate group communications through metacognitive scaffoldings (e.g., monitor and stimulate student tasks) to foster students' cognitive and regulative engagement (Ouyang et al., 2021; Van Leeuwen et al., 2015). In addition, due to the weak connection with the socio-emotional dimension as indicated above, the instructor's social support, such as encouragement and affirmation, might ease the atmosphere and mobilize students' social emotions (Ouyang & Scharber, 2017; Ouyang et al., 2020). Second, instructors are supposed to provide flexible and changeable support (Park et al., 2015; Van de Pol et al., 2010) in terms of student groups' dynamic evolvement in CPS (i.e., from communication to behaviour and back to communication) we detected in the current study. To be specific, in the initial stage, instructors can regulate students to organize discussion about the topic; in the middle stage of online operation, instructors can reduce intervention, observe students, and provide specific support according to the particular needs of the group; in the latter stage, instructors can guide students to solve problems through information relevant to the topic (Kaendler et al., 2015; Ouyang & Xu, 2022; Van Leeuwen et al., 2015). Third, it is challenging to achieve the high-quality synergy between communication and behaviours of student groups. Thus, instructors should pay attention to groups' inactive moments in verbal communication or online behaviour to foster synergistic meaning co-construction (Barron, 2000; Brown et al., 1989; O'Donnell & Hmelo-Silver, 2013). When students only focus on the discussion and neglect operating

the task, the instructor can remind them to return to online operations to drive the task; when students lack enough communication, instructors can guide them to discuss the topics together. Taken together, from a pedagogical perspective, instructors should be aware of groups' dynamic and synergistic status, and support their work appropriately with varied scaffoldings to promote students' CPS.

Limitations and future directions

There were four major limitations in the current research. The first limitation of this research is the sample size of student groups (4 groups generated 24 collaborative activities), with a limited range of demographic backgrounds. The small sample size might be a reason for causing the insignificant differences in the final concept map products. Therefore, future empirical research needs to expand the sample size and experiment with different courses to test, validate, or modify the implications. The second limitation is that we do not control the instructor's participation during the CPS processes. The instructor occasionally participated in the collaboration to provide social, cognitive or regulatory support, which might influence students' collaborative patterns. Due to the authentic and natural instructional context, we cannot control all external factors in the CPS processes; in the future, a quasi-experimental approach can be considered to compare collaborative patterns occurring in two contrasting conditions. The third limitation is that we only collected students' communication discourse and online behaviours to analyze the CPS processes. There are complex, interrelated connections between dimensions. For example, a student's operation on a concept map is coded as the behavioural dimension in the current study, which also involved cognitive and regulative dimensions (e.g., searching for information). Detailed analytics are needed to further uncover complex interrelationships. Moreover, due to the complexity of CPS, other modalities of data (e.g., physiological, and eye tracking data) might provide further insights into CSCL processes. Finally, regarding the AI algorithms, we only used HMMs to detect the temporal patterns in the collaborative process, which might not be the most efficient and accurate algorithm-enabled method. However, this is a significant initial attempt, considering that HMMs have rarely been applied to multichannel social sequence data, especially in the field of education. Future work is encouraged to apply various AI algorithms to compare the relative efficiency and accuracy they might achieve. In addition, other machine learning techniques can be used to guide real-time feedback and predictions of collaboration patterns and outcomes.

Conclusion

Complex adaptive systems theory emphasizes using a multidimensional, microscopic, and nonlinear perspective to explore the complex components and their interactions in a system (Byrne & Callaghan, 2014; Holland, 1996). Because of the complex and adaptive characteristics of the processes involved, CSCL research calls for multi-dimensional, multi-level, and multi-perspective analytical approaches. Addressing the call, this research integrates AI algorithms with learning analytics and various modalities of data to analyze *multimodal*, *dynamic*, and *synergistic* characteristics of collaborative problem-solving. Our findings verify that the method proposed here can indeed be valuable for explorations of CPS from the

complex adaptive systems theory perspective, leading to significant theoretical, analytical, and pedagogical implications.

Data Availability The data is available upon request from the first author.

Declarations

Competing Interest Authors have no competing interests to declare.

References

Abbott, A., & Tsay, A. (2000). Sequence analysis and optimal matching methods in sociology: review and prospect. *Sociological Methods & Research*, *29*(1), 3–33. https://doi.org/10.1177/0049124100029001001.

Amon, M. J., Vrzakova, H., & D'Mello, S. K. (2019). Beyond dyadic coordination: Multimodal behavioral irregularity in triads predicts facets of collaborative problem solving. *Cognitive Science*, *43*(10), https://doi.org/10.1111/cogs.12787. Article e12787.

Barron, B. (2000). Achieving coordination in collaborative problem-solving groups. *Journal of the Learning Sciences*, *9*(4), 403–436. https://doi.org/10.1207/S15327809JLS0904_2.

Blikstein, P. (2013). Multimodal learning analytics. In R. F. Kizilcec, C. Piech, E. Schneider, D. Suthers, K. Verbert, E. Duval, & X. Ochoa (Eds.), *Proceedings of the third international conference on learning analytics and knowledge* (pp. 102–106). ACM. https://doi.org/10.1145/2460296.2460316

Borge, M., & Mercier, E. (2019). Towards a micro-ecological approach to CSCL. *International Journal of Computer-Supported Collaborative Learning*, *14*(2), 219–235. https://doi.org/10.1007/s11412-019-09301-6.

Brown, J. S., Collins, A., & Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher*, *18*(1), 32–42. https://doi.org/10.3102/0013189X018001032.

Byrne, D., & Callaghan, G. (2014). *Complexity theory and the social sciences*. Routledge.

Cress, U., Rosé, C., Wise, A., & Oshima, J. (2021). *International handbook of computer-supported collaborative learning*. Springer.

Cukurova, M., Giannakos, M., & Martinez-Maldonado, R. (2020). The promise and challenges of multimodal learning analytics. *British Journal of Educational Technology*, *51*(5), 1441–1449. https://doi.org/10.1111/bjet.13015.

Curşeu, P. L., Rusu, A., Maricuţoiu, L. P., Vîrgă, D., & Măgurean, S. (2020). Identified and engaged: a multilevel dynamic model of identification with the group and performance in collaborative learning. *Learning and Individual Differences*, *78*, 101838. https://doi.org/10.1016/j.lindif.2020.101838.

Damşa, C. I. (2014). The multi-layered nature of small-group learning: productive interactions in object-oriented collaboration. *International Journal of Computer-Supported Collaborative Learning*, *9*, 247–281. https://doi.org/10.1007/s11412-014-9193-8.

de Carvalho, W. F., & Zárate, L. E. (2020). A new local causal learning algorithm applied in learning analytics. *The International Journal of Information and Learning Technology*, *38*(1), 103–115. https://doi.org/10.1108/IJILT-04-2020-0046.

Dillenbourg, P. (1999). What do you mean by collaborative learning? In P. Dillenbourg (Ed.), *Collaborative-learning: cognitive and computational approaches* (pp. 1–19). Elsevier.

Dindar, M., Järvelä, S., & Haataja, E. (2020). What does physiological synchrony reveal about metacognitive experiences and group performance? *British Journal of Educational Technology*, *51*(5), 1577–1596. https://doi.org/10.1111/bjet.12981.

Eddy, S. R. (1996). Hidden Markov models. *Current Opinion in Structural Biology*, *6*(3), 361–365. https://doi.org/10.1016/S0959-440X(96)80056-X.

Eisenberg-Guyot, J., Peckham, T., Andrea, S. B., Oddo, V., Seixas, N., & Hajat, A. (2020). Life-course trajectories of employment quality and health in the US: a multichannel sequence analysis. *Social Science & Medicine*, *264*, 113327. https://doi.org/10.1016/j.socscimed.2020.113327.

Eloy, L., Stewart, E. B., Jean Amon, A., Reinhardt, M., Michaels, C., Sun, A., & D'Mello, C. (2019). S. Modeling team-level multimodal dynamics during multiparty collaboration. In W. Gao, H. M. L. Meng, M. Turk. R. Fussell, B. Schuller, Y. Song, & K. Yu (Eds.), *2019 International conference on multimodal interaction* (pp. 244–258). ACM. https://doi.org/10.1145/3340555.3353748

Farrokhnia, M., Pijeira-Díaz, H. J., Noroozi, O., & Hatami, J. (2019). Computer-supported collaborative concept mapping: the effects of different instructional designs on conceptual understanding and knowledge co-construction. *Computers & Education*, *142*, Article 103640. https://doi.org/10.1016/j.compedu.2019.103640.

Felsenstein, J., & Churchill, G. A. (1996). A hidden Markov Model approach to variation among sites in rate of evolution. *Molecular Biology and Evolution*, *13*(1), 93–104. https://doi.org/10.1093/oxfordjournals.molbev.a025575.

Fine, S., Singer, Y., & Tishby, N. (1998). The hierarchical hidden Markov model: analysis and applications. *Machine Learning*, *32*, 41–62. https://doi.org/10.1023/A:1007469218079.

Fiore, S. M., Smith-Jentsch, K. A., Salas, E., Warner, N., & Letsky, M. (2010). Toward an understanding of macrocognition in teams: developing and defining complex collaborative processes and products. *Theoretical Issues in Ergonomic Science*, *11*(4), 250–271. https://doi.org/10.1080/14639221003729128.

Gabadinho, A., Ritschard, G., Müller, N. S., & Studer, M. (2011). Analyzing and visualizing state sequences in R with TraMineR. *Journal of Statistical Software*, *40*(4), 1–37. https://doi.org/10.18637/jss.v040.i04.

Gauthier, J. A., Widmer, E. D., Bucher, P., & Notredame, C. (2010). Multichannel sequence analysis applied to social data. *Sociological Methodology*, *40*(1), 1–38. https://doi.org/10.1111/J.1467-9531.2010.01227.X.

Gorman, J. C., Grimm, D. A., Stevens, R. H., Galloway, T., Willemsen-Dunlap, A. M., & Halpin, D. J. (2020). Measuring real-time team cognition during team training. *Human Factors*, *62*(5), 825–860. https://doi.org/10.1177/0018720819852791.

Helske, S., & Helske, J. (2019). Mixture hidden Markov models for sequence data: the seqHMM Package in R. *Journal of Statistical Software*, *88*(3), 1–32. https://doi.org/10.18637/jss.v088.i03.

Hmelo-Silver, C. E. (2004). Problem-based learning: what and how do students learn? *Educational Psychology Review*, *16*, 235–266. https://doi.org/10.1023/B:EDPR.0000034022.16470.f3.

Hmelo-Silver, C. E., & DeSimone, C. (2013). Problem-based learning: an instructional model of collaborative learning. In C. Hmelo-Silver, C. A. Chinn, C. Chan, & A. O'Donnell (Eds.), *The international handbook of collaborative learning*. Routledge.

Holland, J. H. (1996). *Hidden order: how adaptation builds complexity*. Basic Books.

Hoppe, H. U., Doberstein, D., & Hecking, T. (2021). Using sequence analysis to determine the well-functioning of small groups in large online courses. *International Journal of Artificial Intelligence in Education*, *31*, 680–699. https://doi.org/10.1007/s40593-020-00229-9.

Jacobson, M. J., Kapur, M., & Reimann, P. (2016). Conceptualizing debates in learning and educational research: toward a complex systems conceptual framework of learning. *Educational Psychologist*, *51*(2), 210–218. https://doi.org/10.1080/00461520.2016.1166963.

Janssen, J., Cress, U., Erkens, G., & Kirschner, P. A. (2013). Multilevel analysis for the analysis of collaborative learning. In C. E. Hmelo-Silver, C. A. Chinn, C. K. K. Chan, & A. M. O'Donnell (Eds.), *The international handbook of collaborative learning* (pp. 124–137). Routledge.

Jeong, H. (2013). Verbal data analysis for understanding interactions. In C. E. Hmelo-Silver, C. K. K. Chan, C. Chinn, & A. M. O'Donnell (Eds.), *International handbook of collaborative learning* (pp. 168–181). Routledge.

Kaendler, C., Wiedmann, M., Rummel, N., & Spada, H. (2015). Teacher competencies for the implementation of collaborative learning in the classroom: a framework and research. *Educational Psychology Review*, *27*(3), 1–32. https://doi.org/10.1007/s10648-014-9288-9.

Khan, S. M. (2017). Multimodal behavioral analytics in intelligent learning and assessment systems. In A. A. von Davier, M. Zhu, & P. C. Kyllonen (Eds.), *Innovative Assessment of Collaboration* (pp. 173–184). Springer. https://doi.org/10.1007/978-3-319-33261-1_11

Koopmans, M., & Stamovlasis, D. (2016). *Complex dynamical systems in education*. Springer International Publishing.

Krippendorff, K. (2004). Reliability in content analysis: some common misconceptions and recommendations. *Human Communication Research*, *30*(3), 411–433. https://doi.org/10.1093/hcr/30.3.411.

Kuhn, D., Capon, N., & Lai, H. (2020). Talking about group (but not individual) process aids group performance. *International Journal of Computer-Supported Collaborative Learning*, *15*, 179–192. https://doi.org/10.1007/s11412-020-09321-7.

Kwon, K., Liu, Y. H., & Johnson, L. P. (2014). Group regulation and social-emotional interactions observed in computer supported collaborative learning: comparison between good vs. poor collaborators. *Computers & Education*, *78*, 185–200. https://doi.org/10.1016/j.compedu.2014.06.004.

Lansing, J. S. (2003). Complex adaptive systems. *Annual Review of Anthropology*, *32*(1), 183–204. https://doi.org/10.1146/annurev.anthro.32.061002.093440.

Maechler, M., Rousseeuw, P., Struyf, A., Hubert, M., & Hornik, K. (2015). *Cluster: Cluster analysis basics and extensions*. [Software]. R package version 2.0.3.

Malmberg, J., Järvelä, S., & Järvenoja, H. (2017). Capturing temporal and sequential patterns of self-, co-, and socially shared regulation in the context of collaborative learning. *Contemporary Educational Psychology*, *49*, 160–174. https://doi.org/10.1016/j.cedpsych.2017.01.009.

Marquart, C. L., Hinojosa, C., Swiecki, Z., Eagan, B., & Shaffer, D. W. (2018). *Epistemic network analysis* [Software]. Version 1.6.0. Website: epistemicnetwork.org.

Medina, R., & Stahl, G. (2021). Analysis of group practices. In U. Cress, C. Rosé, A. Wise, & J. Oshima (Eds.), *International handbook of computer-supported collaborative learning* (pp. 199–218). Springer.

Mitchell, M. (2009). *Complexity: a guided tour*. Oxford University Press.

Morrison, K. R. B. (2002). *School leadership and complexity theory*. Routledge.

Mu, S., Cui, M., & Huang, X. (2020). Multimodal data fusion in learning analytics: a systematic review. *Sensors (Basel, Switzerland)*, *20*(23), 6856, 1–26. https://doi.org/10.3390/s20236856.

Murtagh, F., & Legendre, P. (2014). Ward's hierarchical agglomerative clustering method: which algorithms implement Ward's criterion? *Journal of Classification*, *31*(3), 274–295. https://doi.org/10.1007/s00357-014-9161-z.

Novak, J. D., & Cañas, A. J. (2008). *The theory underlying concept maps and how to construct and use them*. Florida Institute for Human and Machine Cognition. http://cmap.ihmc.us/Publications/ResearchPapers/TheoryUnderlyingConceptMaps.pdf.

O'Donnell, A. M., & Hmelo-Silver, C. E. (2013). Introduction: what is collaborative learning? An overview. In C. E. Hmelo-Silver, C. A. Chinn, C. K. K. Chan, & A. M. O'Donnell (Eds.), *The international handbook of collaborative learning* (pp. 93–111). Routledge.

Olsen, J. K., Sharma, K., Rummel, N., & Aleven, V. (2020). Temporal analysis of multimodal data to predict collaborative learning outcomes. *British Journal of Educational Technology*, *51*(5), 1527–1547. https://doi.org/10.1111/bjet.12982.

Ouyang, F. (2021). Using three social network analysis approaches to understand computer-supported collaborative learning. *Journal of Educational Computing Research*, *59*(7), 1401–1424. https://doi.org/10.1177/0735633121996477.

Ouyang, F., & Chang, Y. H. (2019). The relationships between social participatory roles and cognitive engagement levels in online discussions. *British Journal of Educational Technology*, *50*(3), 1396–1414. https://doi.org/10.1111/bjet.12647.

Ouyang, F., Chang, Y. H., Scharber, C., Jiao, P., & Huang, T. (2020). Examining the instructor-student collaborative partnership in an online learning community course. *Instructional Science*, *48*(2), 183–204. https://doi.org/10.1007/s11251-020-09507-4.

Ouyang, F., Chen, Z., Cheng, M., Tang, Z., & Su, C. Y. (2021). Exploring the effect of three scaffoldings on the collaborative problem-solving processes in China's higher education. *International Journal of Educational Technology in Higher Education*, *18*(35), 1–22. https://doi.org/10.1186/s41239-021-00273-y.

Ouyang, F., Dai, X., & Chen, S. (2022). Applying multimodal learning analytics to examine the immediate and delayed effects of instructor scaffoldings on small groups' collaborative programming. *International Journal of STEM Education*, *9*(1), 1–21. https://doi.org/10.1186/s40594-022-00361-z.

Ouyang, F., & Scharber, C. (2017). The influences of an experienced instructor's discussion design and facilitation on an online learning community development: a social network analysis study. *The Internet and Higher Education*, *35*, 34–47. https://doi.org/10.1016/j.iheduc.2017.07.002.

Ouyang, F., Wu, M., Zhang, L., Xu, W., Zheng, L., & Cukurova, M. (2023). Making strides towards AI-supported regulation of learning in collaborative knowledge construction. *Computers in Human Behavior*, *142*, 107650. https://doi.org/10.1016/j.chb.2023.107650.

Ouyang, F., & Xu, W. (2022). The effects of three instructor participatory roles on a small group's collaborative concept mapping. *Journal of Educational Computing Research*, *60*(4), 930–959. https://doi.org/10.1177/07356331211057283.

Park, J. B. H., Schallert, D. L., Sanders, A. J. Z., Williams, K. M., Seo, E., Yu, L. T., Vogler, J. S., Song, K., Williamson, Z. H., & Knox, M. C. (2015). Does it matter if the teacher is there? A teacher's contribution to emerging patterns of interactions in online classroom discussions. *Computers & Education*, *82*, 315–328. https://doi.org/10.1016/j.compedu.2014.11.019.

Ramenzoni, V. C., Riley, M. A., Shockley, K., & Baker, A. A. (2012). Interpersonal and intrapersonal coordinative modes for joint and single task performance. *Human Movement Science*, *31*(5), 1253–1267. https://doi.org/10.1016/j.humov.2011.12.004.

Rogat, T. K., & Adams-Wiggins, K. R. (2015). Interrelation between regulatory and socioemotional processes within collaborative groups characterized by facilitative and directive other-regulation. *Computers in Human Behavior*, *52*, 589–600. https://doi.org/10.1016/j.chb.2015.01.026.

Roschelle, J., & Teasley, S. D. (1995). The construction of shared knowledge in collaborative problem solving. In C. O'Malley (Eds.), *Computer supported collaborative learning* (pp. 69–97). Springer. https://doi.org/10.1007/978-3-642-85098-1_5

Saqr, M., & López-Pernas, S. (2022). How CSCL roles emerge, persist, transition, and evolve over time: a four-year longitudinal study. *Computers & Education*, *189*, https://doi.org/10.1016/j.compedu.2022.104581. Article 104581.

Saqr, M., Peeters, W., & Viberg, O. (2021). The relational, co-temporal, contemporaneous, and longitudinal dynamics of self-regulation for academic writing. *Research and Practice in Technology Enhanced Learning, 16*(1), 1–22. https://doi.org/10.1186/s41039-021-00175-7Schindler, M., & Bakker, A. (2020). Affective field during collaborative problem posing and problem solving: A case study. *Educational Studies in Mathematics, 105*(3), 303–324. https://doi.org/10.1007/s10649-020-09973-0

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

Sharma, K., & Giannakos, M. (2020). Multimodal data capabilities for learning: what can multimodal data tell us about learning? *British Journal of Educational Technology*, *51*(5), 1450–1484. https://doi.org/10.1111/bjet.12993.

Stahl, G. (2009). *Studying virtual math teams*. Springer.

Stahl, G. (2013). Learning across levels. *International Journal of Computer-Supported Collaborative Learning*, *8*(1), 1–12. https://doi.org/10.1007/s11412-013-9169-0.

Stahl, G. (2017). Group practices: A new way of viewing CSCL. *International Journal of Computer-Supported Collaborative Learning, 12*(1), 113–126.10.1007/s11412-017-9251-0

Stahl, G., & Hakkarainen, K. (2021). Theories of CSCL. In U. Cress, C. Rosé, A. F. Wise, & J. Oshima (Eds.), *International handbook of computer-supported collaborative learning* (pp. 23–44). Springer. https://doi.org/10.1007/978-3-030-65291-3_2

Sullivan, F. R., & Keith, P. K. (2019). Exploring the potential of natural language processing to support microgenetic analysis of collaborative learning discussions. *British Journal of Educational Technology*, *50*(6), 3047–3063. https://doi.org/10.1111/bjet.12875.

Van de Pol, J., Volman, M., & Beishuizen, J. (2010). Scaffolding in teacher–student interaction: a decade of research. *Educational Psychology Review*, *22*, 271–296. https://doi.org/10.1007/s10648-010-9127-6.

Van Leeuwen, A., Janssen, J., Erkens, G., & Brekelmans, M. (2015). Teacher regulation of cognitive activities during student collaboration: Effects of learning analytics. *Computers & Education*, *90*(1), 80–94. https://doi.org/10.1016/j.compedu.2015.09.006.

Vogler, J. S., Schallert, D. L., Jordan, M. E., Song, K., Sanders, A. J., Chiang, T., & Yu, Y. H. Y., L. T (2017). Life history of a topic in an online discussion: a complex systems theory perspective on how one message attracts class members to create meaning collaboratively. *International Journal of Computer-Supported Collaborative Learning*, *12*(2), 173–194. https://doi.org/10.1007/s11412-017-9255-9.

Vrzakova, H., Amon, M. J., Stewart, A., Duran, N. D., & D'Mello, S. K. (2020). Focused or stuck together: Multimodal patterns reveal triads' performance in collaborative problem solving. In C. Rensing, & H. Drachsler (Eds.), *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 295–304). ACM. https://doi.org/10.1145/3375462.3375467

Vygotsky, L. S. (1978). *Mind in society: the development of higher psychological processes*. Harvard University Press.

Wang, M., Cheng, B., Chen, J., Mercer, N., & Kirschner, P. A. (2017). The use of web-based collaborative concept mapping to support group learning and interaction in an online environment. *Internet and Higher Education*, *34*, 28–40. https://doi.org/10.1016/j.iheduc.2017.04.003.

Wiltshire, T. J., Steffensen, S. V., & Fiore, S. M. (2019). Multiscale movement coordination dynamics in collaborative team problem solving. *Applied Ergonomics*, *79*, 143–151. https://doi.org/10.1016/j.apergo.2018.07.007.

Wise, A. F., Knight, S., & Shum, S. B. (2021). Collaborative learning analytics. In U. Cress, C. Rosé, A. F. Wise, & J. Oshima (Eds.), *International handbook of computer-supported collaborative learning* (pp. 425–444). Springer. https://doi.org/10.1007/978-3-030-65291-3_23

Xu, W., & Ouyang, F. (2022). A systematic review of AI role in the educational system based on a proposed conceptual framework. *Education and Information Technologies*, *27*, 4195–4223. https://doi.org/10.1007/s10639-021-10774-y.

Zemel, A., & Koschmann, T. (2013). Recalibrating reference within a dual-space interaction environment. *International Journal of Computer-Supported Collaborative Learning*, *8*(1), 65–87. https://doi.org/10.1007/s11412-013-9164-5.

Zhang, J. (2007). A cultural look at information and communication technologies in eastern education. *Educational Technology Research and Development*, *55*(3), 301–314. https://doi.org/10.1007/s11423-007-9040-y.

Zhang, J. (2013). Chapter 28: collaboration, technology, and culture. In C. E. Hmelo-Silver, C. A. Chinn, C. K. K. Chan, & A. M. O'Donnell (Eds.), *The international handbook of collaborative learning* (pp. 495–508). New York, NY: Routledge.

Zheng, L., Zhong, L., Niu, J., Long, M., & Zhao, J. (2021). Effects of personalized intervention on collaborative knowledge building, group performance, socially shared metacognitive regulation, and cognitive load in computer-supported collaborative learning. *Educational Technology & Society*, *24*(3), 174–193. https://www.jstor.org/stable/27032864.

Zuiker, S. J., Anderson, K. T., Jordan, M. E., & Stewart, O. G. (2016). Complementary lenses: using theories of situativity and complexity to understand collaborative learning as systems-level social activity. *Learning Culture and Social Interaction*, *9*, 80–94. https://doi.org/10.1016/J.LCSI.2016.02.003.