Using a three-layered social-cognitive network analysis framework for understanding online collaborative discussions

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Understanding the relationship between social and cognitive engagement has critical implications for collaborative learning theory, pedagogy and analytics. This study proposed a three-layered social-cognitive network analysis framework for examining the relationship between students' social and cognitive engagement from summative, epistemic and micro-level perspectives within online collaborative discussions. A multi-method approach was used, consisting of social network analysis, quantitative content analysis, statistical analysis, epistemic network analysis and social-cognitive network visualisation. The results showed that from a summative perspective, students' social participatory roles were critical indicators of their level of cognitive engagement. From an epistemic perspective, socially active students tended to shift towards more group-level cognitive structure, while inactive students showed a decreasing individual-level cognitive structure throughout the discussion duration. From a micro-level perspective, a large proportion of individual students showed continually changing social participatory roles with fluctuating cognitive engagement levels. The findings have implications for collaborative learning theory, pedagogy support and learning analytics.

Implications for practice or policy:

- Researchers can use the three-layered social-cognitive network analysis framework to examine student engagement.
- Instructors should encourage student agency for facilitating high-quality online collaborative discussion.
- Instructors should consider students' different engagement levels in online discussions.

Keywords: online collaborative discussion, social learning analytics, three-layered social-cognitive network analysis framework, multi-method approach, computer-supported collaborative learning

Introduction

Grounded in socio-cognitive constructivism (De Lisi & Golbeck, 1999; Doise et al., 1975; Glasersfeld, 1987), learning is a social-cognitive process supported by purposeful instructions and technologies and formed through emergent learner interactions and communications (Brown et al., 1989). Such attributes manifest during online collaborative discussions where students share, construct and reflect on knowledge through social interactions in asynchronous or synchronous ways (Damsa, 2014; Ouyang & Chang, 2019; van Aalst, 2009). From a theoretical perspective, there is a close relationship between social and cognitive engagement: changes and developments in one influence the other (Liu & Matthews, 2005). From an educational perspective, this relationship is of critical importance for instructional design and development in online collaborative learning (Ouyang & Chang, 2019). However, empirical research has indicated a complex relationship between social and cognitive engagement. Some studies have found no direct relationship between social and cognitive engagement (e.g., S. Zhang et al., 2017), whereas others have demonstrated a positive relationship between them (e.g., Rolim et al., 2019). Moreover, several studies have indicated that socially inactive or low-performing students also occasionally contribute to deep-level cognitive inquiry (Ouyang & Chang, 2019; Saqr et al., 2020; Vaquero & Cebrian, 2013). Given the complexity of the relationships, it is necessary to further examine the relationship between social and cognitive engagement. This study proposed a three-layered social-cognitive network analysis (SCNA) framework, supported by a multi-method approach, to examine the relationship between social and cognitive engagement from summative, epistemic and micro-level perspectives. The results of this study have implications for enhancing collaborative learning theory, pedagogy support and learning analytics.

Literature review

Online collaborative discussion primarily involves three constructs: individual learners' knowledge inquiry, social interaction processes, and knowledge construction at the group or class level (Damsa, 2014; Liu & Matthews, 2005; Scardamalia, 2002). Social and cognitive engagement emerges during the collaborative process: social engagement refers to students' social interactions when they respond or reply to a peer's ideas and perspectives (Ouyang & Scharber, 2017), and cognitive engagement refers to students' individual knowledge inquiry and group knowledge advancement through peer interactions (Damşa, 2014). The theoretical foundation indicates a critical relationship between social and cognitive engagement: they are usually closely interconnected, functionally unified, and mutually developed (Liu & Matthews, 2005). To develop high quality online discussion, students usually need to maintain peer interactions to respond to others' ideas and make substantial cognitive contributions (Ouyang & Chang, 2019; Salter & Conneely, 2015; Yücel & Usluel, 2016). Moreover, students with different social engagement levels (e.g., social interaction frequency) tend to vary in cognitive engagement, contribution or structure (Ouyang & Chang, 2019; J. Zhang et al., 2020). For example, socially active students are more likely to maintain interactions with peers to share, spread and receive ideas, while socially inactive students are more likely to become marginal and fail to contribute significantly (Ouyang & Chang, 2019; Ouyang et al., 2021). Therefore, the way students build social relations to some extent influences their cognitive engagement in knowledge sharing, construction and creation (Ouyang & Chang, 2019; Rolim et al., 2019; van Aalst, 2009).

However, relevant empirical research reveals contradictory findings about the relationship between social and cognitive engagement. Social network analysis (SNA) and content analysis (CA) are two primary methods used to examine social and cognitive engagement (Cohen et al., 2013). SNA is used to analyse social relations, their characteristics, and their influence on learning (de Laat et al., 2007), while CA is used to examine the cognitive aspects of learning, such as individual cognitive inquiry (e.g., Garrison et al., 2001) and group knowledge construction (e.g., Häkkinen, 2013). Some studies using these methods found no direct relationship between social and cognitive engagement. For example, Zhu (2006) found that groups with different social network structures (e.g., a star network concentrated on one person or an interconnected network distributed across all persons) had no relationship with students' cognitive engagement. In an investigation of schoolteachers' social and cognitive engagement in online learning, S. Zhang et al. (2017) found no significant difference in knowledge construction patterns between core members (i.e., extremely active members located at the centre of the network) and peripheral members (i.e., inactive members located at the periphery of the network). In contrast, other studies demonstrated positive relationships between participants' social and cognitive engagement. For example, Rolim et al. (2019) examined relationships between social and cognitive presences in an online asynchronous discussion. Their results showed that affective indicators of social presence had stronger connections with two high levels of cognitive presence (i.e., integration and resolution), while interactive indicators of social presence were more connected to two low levels of cognitive presence (i.e., triggering events and exploration). Gašević et al. (2017) examined the relationship between students' discussion content and communication roles in a massive open online course forum. The results indicated that students who focused on the topics highly connected to the course content played the most central roles, while students whose content had little relationship with topics were positioned on the periphery of the discussions. Overall, contradictory results have been found regarding relationships between social and cognitive engagement.

One major cause of these contradictory results is the focus on summative, macro-level analysis and a lack of micro-level temporal analysis. A macro-level analysis might overlook the finer details of the changing dynamics in collaborative groups. Because collaborative learning occurs through progressive, interactive dialogues over time (Chen et al., 2017), it was critical to investigate its temporal, process-oriented aspects (Kapur, 2011). To unpack the trajectory of a collaborative process, it was necessary to examine the sequential temporal relations between social and cognitive engagement in online collaborative discussions (e.g., Csanadi et al., 2018). For example, Ouyang and Scharber (2017) examined changes in the social networks in an online class and dynamic changes of the instructor's roles throughout the formation of an online learning community. Taking time as a critical variable, Chen et al. uncovered sequential transitional patterns that distinguished productive threads of the knowledge-building discourses in Knowledge Forum that quantitative coding and counting methods might obscure. Shaffer's research team proposed the epistemic network analysis (ENA) method, which used mathematic algorithms to calculate the connections between the coded data of concepts, keywords or ideas within given texts, visualised them in dynamic network models and illustrated the changes in structures and connection strength over time (Shaffer et al., 2009; Shaffer et al., 2016; Shaffer & Ruis, 2017). The ENA approach is grounded in the idea that the connective structure between cognitive elements is more important than the presence of these elements alone and therefore stresses analysis of the structures and patterns of connections between knowledge, skills and other elements to characterise collaborative learning. Overall, given the complexity and nuances of collaborative learning, it is necessary to examine the relationships between social and cognitive engagement from a temporal, micro-level perspective.

Moreover, SNA and CA have recently been used in innovative, integrated ways to examine the relationship between social and cognitive engagement in online collaborative learning. For example, Knowledge Building Discourse Explorer, an SNA application for knowledge building, aimed to integrate text mining techniques and network representations, to extract networks of concepts from a given discussion or discourse transcripts, and to demonstrate the relations between these concepts or ideas (Matsuzaw et al., 2011; Oshima et al., 2012). The results suggested that this integrated method qualitatively and quantitatively analysed collaborative knowledge building discourses, revealed potential pivotal points for social knowledge advancement in groups, and identified each individual's cognitive contribution to this advancement (Oshima et al., 2012). Moreover, Ouyang and Chang (2019) designed social-cognitive network visualisation (SCNV) to demonstrate both social interactions (e.g., participatory role, network position, interaction frequency) and cognitive engagement (e.g., knowledge inquiry, knowledge construction). This innovative social-cognitive network representation successfully tracked individual students' social interaction patterns and cognitive engagement levels, revealing details that statistical or summative analysis cannot. The idea-friend map design of Feng et al. (2019) showed words that had or had not been discussed by the group members. Students in different groups then identified idea friends via the map, made connections between different science concepts, and interacted with different groups to advance their collective knowledge. Therefore, integrated methods can reveal a richer, more detailed picture of online collaborative learning that one method alone is unlikely to achieve. Following this research trend, this study proposed and applied a three-layered SCNA framework supported by a multi-method approach to examine the relationship between social and cognitive engagement in online collaborative discussions.

Methodology

Research purposes and questions

The purpose of this study was to achieve a deep, multidimensional understanding of the relationship between social and cognitive engagement in online collaborative discussions and then to identify the theoretical, pedagogical, and analytical implications based on empirical evidence. To achieve these purposes, this study proposed a three-layered SCNA framework supported by a multi-method approach to examine the relationship between social and cognitive engagement from summative, epistemic and micro-level perspectives. The research question was "What was the relationship between students' social participatory roles and cognitive engagement levels during online collaborative discussions?"

Research context and participants

The research context was an undergraduate-level, 2-semester (16-week) course titled Modern Educational Technologies offered in the spring and summer semesters of 2020 at a top research-intensive university in China. The course focused on learning theories, instructional design, educational technologies, emerging tools, and trending topics. The course was typically offered in a face-to-face classroom environment; however, because of COVID-19, all courses were moved online using the XueZaiZheDa online learning management system and DingTalk videoconferencing software. The course was co-taught by three instructors (one being the first author), who facilitated different weekly topics. A total of 69 undergraduate students (51 females, 18 males) were enrolled. A typical instructional procedure started with an instructor delivering an online lecture, followed by synchronous class-level discussions. One of us (the first author) designed two major after-class learning activities. During the first 8 weeks, students were randomly assigned to three large groups to continue their collaborative discourse through asynchronous discussions in the XueZaiZheDa forum after the class (see Figure 1). During the last 8 weeks, the students were divided into 18 small groups to complete collaborative writing activities on emerging educational technology topics. For this, they created small groups in DingTalk to discuss the topic in a synchronous format (see Figure 2). The idea-centred knowledge building pedagogy was used to foster student engagement in discussions (Hong & Sullivan, 2009). For example, in the large-group forum discussion, the instructor posted several open-ended prompting questions related to the weekly topic, asked students to elaborate on their perspectives, and encouraged them to build on, critique or reflect on the others' ideas. In the small-group synchronous discussions, the students were also encouraged to share and build knowledge without the instructor's presence.

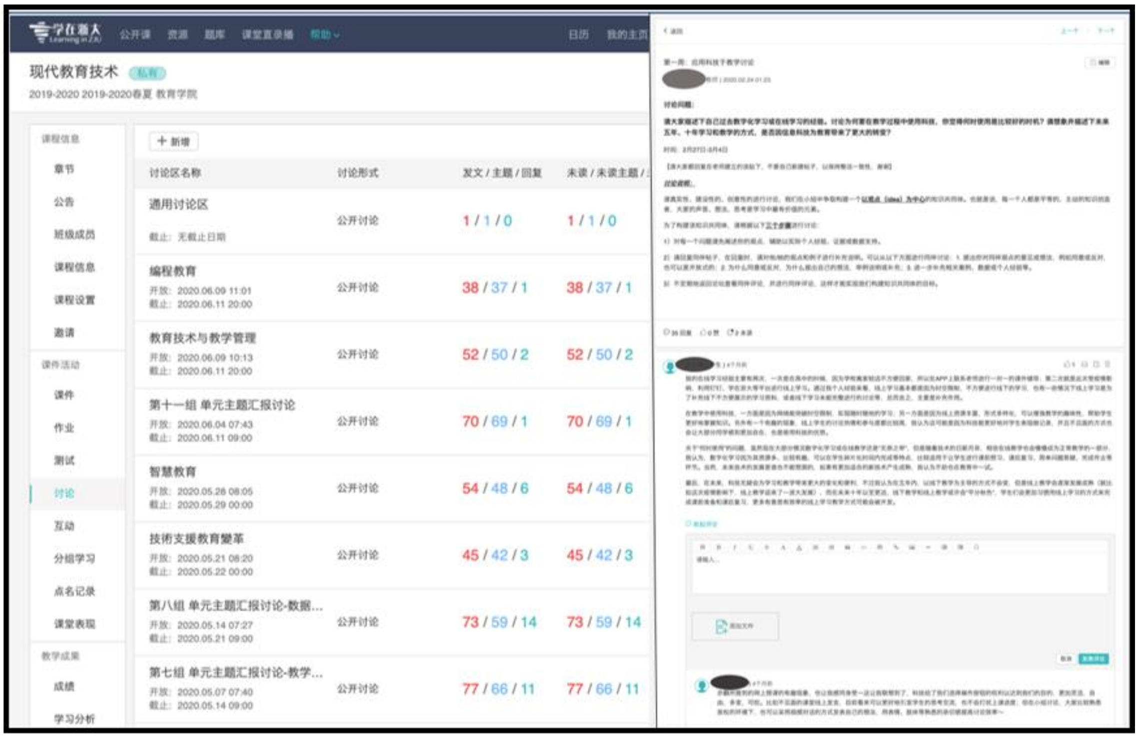


Figure 1. Screenshots from the XueZaiZheDa forum

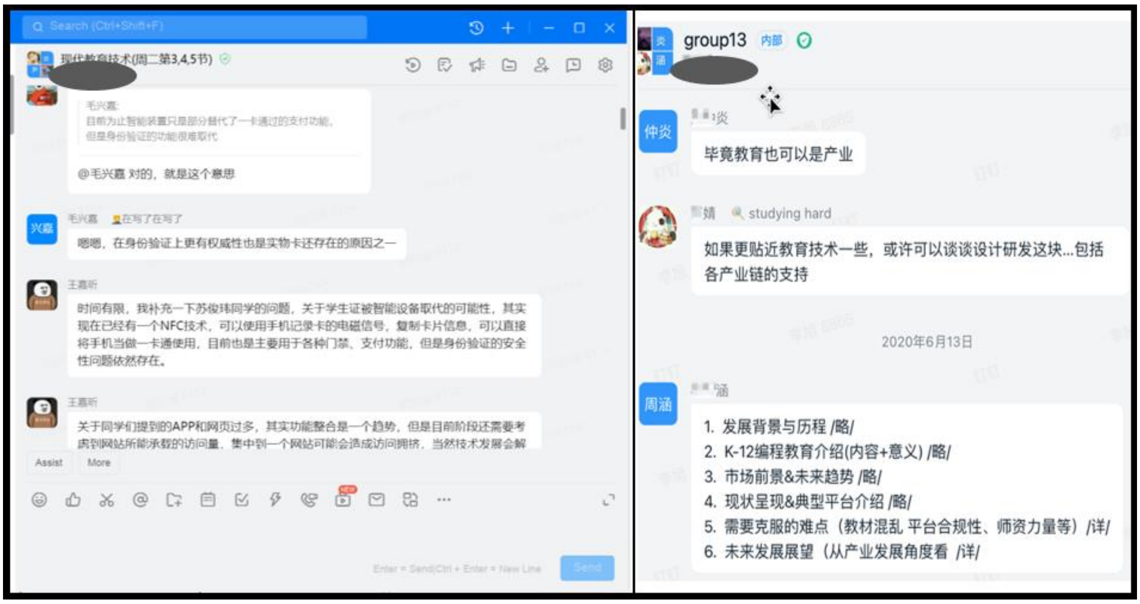


Figure 2. Screenshots of class-level and group-level discussions in DingTalk

Data collection

Online discussion data were collected after the course in an unobtrusive way (students were not required to post a specific number of replies or comments), including the class-level synchronous discussions in DingTalk (Weeks 1–16), online asynchronous discussions in the XueZaiZheDa forum (Weeks 1–8), and small-group synchronous discussions in DingTalk (Weeks 9–16). The overall data set comprised 1,068 student-student interactions and 2,472 comments (see Table 1). The data set was divided into eight data sets or phases (2 weeks per phase), including eight matrices of direct student-student interactions with comment content. This study was exempt from the Research Ethics Committee of Zhejiang University. All names used in this article were anonymised.

Table 1
Descriptive statistics for the eight phases

	Phase 1 *N* = 63	Phase 2 *N* = 59	Phase 3 *N* = 62	Phase 4 *N* = 59	Phase 5 *N* = 67	Phase 6 *N* = 62	Phase 7 *N* = 57	Phase 8 *N* = 55
No. of initial comments per student	3.06 (1.74)	1.95 (0.74)	3.05 (1.28)	2.63 (1.88)	4.82 (4.03)	2.35 (1.66)	2.18 (4.29)	2.87 (2.34)
No. of peer responses per student	2.37 (4.45)	0.78 (1.39)	1.58 (2.42)	1.36 (2.21)	4.27 (5.55)	3.50 (7.23)	1.46 (2.27)	1.98 (3.08)

Note. Mean (standard deviation) were demonstrated; *N* represents the number of students who participated in discussions during a given phase. There were 484 participants across the eight phases. Students who did not participate at all were excluded.

The proposed analytical framework, methods and procedures

A three-layered SCNA framework was proposed to examine the relationships between students' social participatory roles and cognitive engagement levels from summative, epistemic and micro-level perspectives (see Figure 3). The primary analytical methods consisted of SNA and CA. Grounded upon graph theory, SNA analyses relations among entities, the characteristics of those relations and the influences of those relations (Cohen et al., 2013). A social network is represented in graphics with entities (e.g., individuals, groups, resources, events) denoted as nodes with sizes, and relations between entities denoted as ties, with strengths and directions. CA is a research technique for the systematic, objective and quantitative description of the manifest content of communication through segmenting communication content into units, assigning each unit to a category, and providing tallies for each category (Cohen et al., 2013). Based on those two primary analytical results, each student's social participatory roles and cognitive engagement levels were identified in eight phases. Furthermore, a three-layered SCNA framework was proposed (see Figure 3). Specifically, statistical analysis (SA), ENA and SCNV were used to answer the research question from summative, epistemic and micro-level perspectives. SA included descriptive and correlation statistics. ENA calculated the connections between the coded results of CA, visualised them in network models, and illustrated the changes in structures and connection strength over time. The SCNV demonstrated each individual student's social participatory roles and cognitive engagement levels to reveal details of the changes. The detailed analysis procedures involved three steps, as described below.

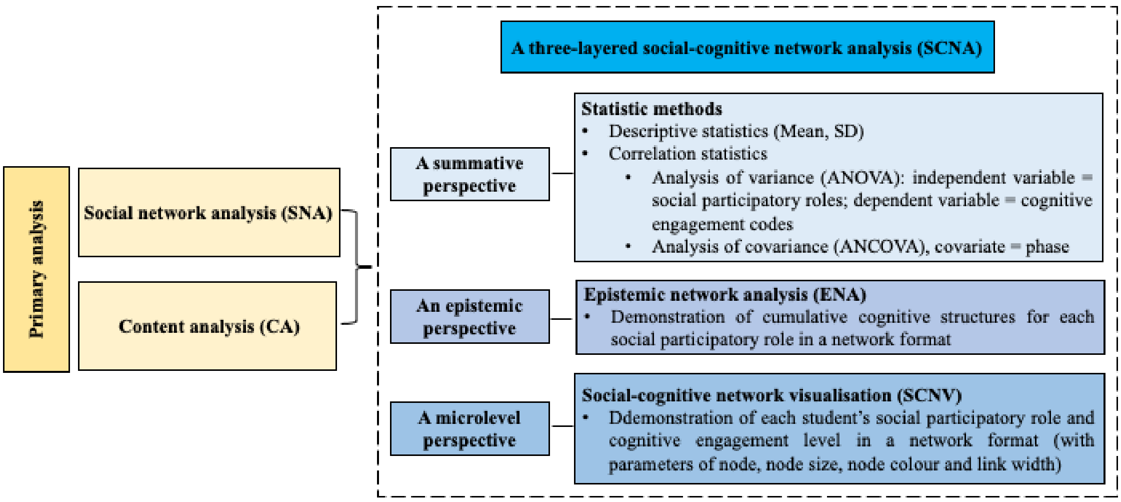


Figure 3. The proposed analytical framework

Step 1: Identifying each student's social participatory roles in each phase

The students' social engagement was reflected by their social participatory role in each phase. A previously validated SNA method was used to identify these roles (see Ouyang & Chang, 2019). The SNA centralities, namely outdegree, indegree, outcloseness, incloseness and betweenness, were used to identify six roles, that is, *leader*, *starter*, *influencer*, *mediator*, *regular* and *peripheral*. Previous studies have argued that the measurement of relational ties has a critical effect on the research results (Chiu et al., 2014; Fincham et al., 2018; Ouyang & Scharber, 2017; Wise & Cui, 2018). In this study, Opsahl's α value of 0.5 was used to measure the SNA centralities. With this measure, both the effect of the number of students (i.e., number of ties) and the interaction frequency (i.e., tie weights) were considered in the SNA metrics (Opsahl, 2009; Opsahl et al., 2010; Opsahl & Panzarasa, 2009). This measure can generate a more accurate result for collaborative learning research compared with only the number of students or the overall interaction frequency (Ouyang, 2021; Ouyang & Chang, 2019; Ouyang & Scharber, 2017). Next, the six social participatory roles were identified in terms of high, medium, and low levels of participation (reflected by outdegree and outcloseness), influence (reflected by indegree and incloseness) and mediation (reflected by betweenness) (see Table 2). A student's centrality score (e.g., outdegree) of 0%–20% was categorised as low, 21%–80% was categorised as medium, and 81%–100% was categorised as high. After calculating the SNA centrality scores and ranges, the students' social participatory roles were identified for each phase. A leader had high participation, influence, and mediation (at least two of these were high). A starter had high participation but medium to low influence and mediation. An influencer had high influence but medium to low participation and mediation. A mediator had high mediation. A regular student had medium participation, influence, and mediation. A peripheral student had low participation, influence, and mediation (at least two of these were low).

Table 2
Social participatory role detection method (Ouyang & Chang, 2019, p. 1402)

	Participation		Influence		Mediation
	outdegree	outcloseness	indegree	incloseness	betweenness
Leader	H or M	H or M	H or M	H or M	H or M
Starter	H	H	L or M	L or M	L or M
Influencer	L or M	L or M	H	H	L or M
Mediator	L or M	L or M	L or M	L or M	H
Regular	M	M	M	M	M
Peripheral	L or M	L or M	L or M	L or M	L or M

Step 2: Identifying each student's cognitive engagement levels in each phase

CA was used to identify the cognitive engagement level of the students' comment content based on a previously validated coding framework (see Table 3). This coding framework consisted of a three-level knowledge inquiry (KI) category (capturing individual cognitive inquiry in students' initial comments) and a three-level knowledge construction (KC) category (capturing group knowledge advancement in the students' responses) (Ouyang & Chang, 2019). The unit of analysis was a full sentence in a synchronous chat and a paragraph in the asynchronous forum. Three trained raters coded the whole data set separately, and they reached an inter-rater reliability of Cohen's kappa = 0.895. The first author checked the conflicting codes and made the final decisions. Next, the cognitive engagement levels were calculated as weighted scores, including the weighted KI score (i.e., a weighted KI score = SKI*1 + MKI*2 + DKI*3) and the weighted KC score (i.e., a weighted KC score = SKC*1 + MKC*2 + DKC*3). At the end of Step 2, eight matrix data sets (one for each phase) were created that included the directed student–student interactions (i.e., who replied to whom), the content of the comments or replies, the identified social participatory role of each student in each phase, and the coded cognitive engagement level of each comment.

Table 3
The cognitive engagement framework (Ouyang & Chang, 2019, p. 1404)

Category	Code	Level	Description
Knowledge inquiry (KI)	Superficial-level knowledge inquiry (*SKI*)	1	A participant explores information related to the discussion topics without explicitly stating his/her own ideas, arguments, or perspectives.
	Medium-level knowledge inquiry (*MKI*)	2	A participant presents his/her own ideas, arguments, or perspectives without a detailed explanation or supporting resources, statistics, or personal experience.
	Deep-level knowledge inquiry (*DKI*)	3	A participant explicitly elaborates his/her own ideas, arguments, or perspectives with a detailed explanation or supporting resources, statistics, or personal experience.
Knowledge construction (KC)	Superficial-level knowledge construction (*SKC*)	1	A participant simply presents (dis)agreement, asks questions, or seeks clarification without explicitly stating his/her own ideas, arguments, or perspectives.
	Medium-level knowledge construction (*MKC*)	2	A participant extends another participant's ideas, arguments, or perspectives with a detailed explanation or supporting information, resources, statistics, or personal experience.
	Deep-level knowledge construction (*DKC*)	3	A participant extends, connects, and deepens the ideas, arguments, or perspectives proposed by other participants with detailed explanations or supporting information, resources, statistics, or personal experience.

Note. Students' comments and responses unrelated to cognitive engagement with the discussion topics (e.g., social information sharing) were excluded from the analysis.

Step 3: Examining the relationship between social participatory roles and cognitive engagement levels
A three-layered SCNA framework was proposed and applied to examine the relationship between the social participatory roles and cognitive engagement levels in a temporal, phase-based fashion. The multi-method approach consisted of statistical analysis, ENA and SCNV. The first layer took a summative perspective, applying statistical analysis to numerically represent the cognitive contributions of students with different social participatory roles. Descriptive statistics (mean, standard deviation), analysis of variance (ANOVA), and analysis of covariance (ANCOVA) were used to examine whether the social participatory roles could predict the cognitive engagement levels. Post-hoc tests were conducted to compare whether there were statistically significant differences between any two roles. The second layer took an epistemic perspective, utilising ENA to represent the cognitive structures of students with different social participatory roles (Shaffer et al., 2016). ENA was used to further examine the cumulative cognitive structures of each role through eight phases (Shaffer et al., 2016). An ENA Webkit (https://epistemicnetwork.org/) was used to perform the ENA analysis and visualisation (Shaffer et al., 2016). The ENA network plots indicated a similar cognitive structure when the means of the centroids were positioned close to each other and a different cognitive structure when the mean of the centroids were positioned far from each other (see details in Figure 4). The third layer used a micro-level perspective to apply SCNV to represent the changes in the cognitive engagement levels of individual students. A network visualisation approach was used to track each student's social participatory role and cognitive engagement level in order to show whether individual students made consistent or variable cognitive contributions throughout the course (see Ouyang & Chang, 2019, for details). In this network visualisation, the node size represented a student's weighted knowledge inquiry score, the link width represented the student's weighted knowledge construction score and the node colours represented the six social participatory roles (see details in Figure 5).

Results

SCNA layer 1: The summative perspective

There were 4,473 cognitive codes: 976 SKI (21.82%), 1,727 MKI (38.61%), 309 DKI (6.91%), 500 SKC (11.18%), 773 MKC (17.28%), and 188 DKC (4.20%). Of the 484 participations across the eight phases, 74 were from leader students (15.29%), 26 from starter students (5.37%), 30 from influencer students (6.20%), 34 from mediator students (7.03%), 93 from regular students (19.21%) and 227 from peripheral students (46.90%) (see Table 4).

ANOVA results showed that there were statistically significant differences between six social participatory roles on SKI ($F = 27.76$, $p < .001$), MKI ($F = 40.62$, $p < .001$), DKI ($F = 10.11$, $p < .001$), SKC ($F = 11.13$, $p < .001$), MKC ($F = 44.22$, $p < .001$) and DKC ($F = 4.37$, $p < .001$). Post-hoc tests indicated that there were statistically significant differences ($p < .001$) between leader and peripheral, mediator and peripheral, starter and peripheral as well as regular and peripheral on SKI. For MKI, significant differences were found between leader and influencer, leader and peripheral, mediator and influencer, influencer and regular, mediator and peripheral, starter and peripheral as well as regular and peripheral. For DKI, there were significant differences between leader and influencer as well as mediator and peripheral. For SKC, there were significant differences between starter and peripheral as well as regular and peripheral. For MKC, there were significant differences between leader and starter, leader and regular, leader and peripheral, influencer and peripheral, mediator and peripheral, regular and peripheral as well as starter and peripheral. For simplicity, results of significant differences ($p < .05$ and $p < .01$) are not shown here or below).

The ANOVA results also showed statistically significant differences of social participatory roles on weighted KI ($F = 53.17$, $p < .001$) and weighted KC ($F = 62.58$, $p < .001$) scores. For weighted KI, there were statistically significant differences ($p < .001$) on SKI between leader and influencer, leader and peripheral, mediator and influencer, mediator and peripheral, regular and influencer, regular and peripheral, and starter and peripheral. For weighted KC, there were statistically significant differences between leader and peripheral, influencer and peripheral, mediator and peripheral, starter and peripheral, and regular and peripheral.

The ANCOVA results showed that taking *phase* as a covariate, there were statistically significant differences of six social participatory roles on six codes, namely SKI ($F = 29.48$, $p < .001$), MKI ($F = 54.55$, $p < .001$), DKI ($F = 11.97$, $p < .001$), SKC ($F = 12.10$, $p < .001$), MKC ($F = 45.32$, $p < .001$) and DKC ($F = 4.40$, $p < .001$) (see Table 3). Post-hoc tests indicated that there were statistically significant differences ($p < .001$) between leader and peripheral, mediator and peripheral, starter and peripheral, and regular and peripheral on SKI. For MKI, significant differences were found between leader and peripheral, mediator and peripheral, starter and peripheral, regular and peripheral, leader and influencer, influencer and mediator, and influencer and regular. For DKI, there were significant differences between leader and peripheral, mediator and peripheral, and starter and peripheral. For SKC, there were significant differences between starter and peripheral. For MKC, there were significant differences between leader and peripheral, regular and peripheral, leader and regular, and mediator and peripheral. For simplicity, results of significant differences ($p < .05$ and $p < .01$) are not shown here or below. The ANCOVA results also showed that the social participatory roles were statistically significant for the weighted KI ($F = 72.37$, $p < .001$) and KC scores ($F = 63.49$, $p < .001$). For weighted KI, there were statistically significant differences ($p < .001$) on SKI between leader and peripheral, starter and peripheral, mediator and peripheral, regular and peripheral, leader and influencer, influencer and mediator, and influencer and regular. For weighted KC, there were statistically significant differences between leader and peripheral, starter and peripheral, mediator and peripheral, regular and peripheral.

Table 4
Descriptive statistics (mean, SD) of the cognitive engagement codes for the six roles

	Leader (N = 74)	Starter (N = 26)	Influencer (N = 30)	Mediator (N = 34)	Regular (N = 93)	Peripheral (N = 227)	ANOVA		ANCOVA	
							F	p	F	p
SKI	2.50 (2.45)	2.31 (2.49)	2.37 (2.73)	1.29 (0.96)	1.76 (2.49)	1.99 (2.32)	27.76	< .001 ***	29.48	< .001 ***
MKI	4.97 (4.72)	4.88 (4.23)	5.63 (4.86)	2.03 (3.17)	2.24 (3.25)	3.46 (4.50)	40.62	< .001 ***	54.55	< .001 ***
DKI	0.84 (1.33)	0.88 (1.22)	0.53 (1.23)	0.21 (0.63)	0.97 (1.53)	0.49 (1.10)	10.11	< .001 ***	11.97	< .001 ***
Weighted KI	14.96 (11.08)	14.73 (10.86)	15.23 (12.12)	5.97 (7.71)	9.14 (9.76)	10.38 (10.62)	53.17	< .001 ***	72.37	< .001 ***
SKC	2.43 (3.50)	2.96 (8.38)	0.83 (2.42)	1.26 (1.61)	1.32 (2.36)	0.23 (0.62)	11.13	< .001 ***	12.10	< .001 ***
MKC	5.49 (5.11)	2.42 (1.84)	1.27 (2.32)	1.74 (1.72)	1.83 (3.19)	0.16 (0.46)	44.22	< .001 ***	45.32	< .001 ***
DKC	1.03 (1.51)	0.85 (1.70)	0.20 (0.48)	0.35 (0.72)	0.60 (1.22)	0.07 (0.27)	4.37	< .001 ***	4.40	< .001 ***
Weighted KC	16.49 (13.62)	10.35 (11.68)	3.97 (5.71)	5.79 (4.79)	6.78 (9.66)	0.77 (1.63)	62.58	< .001 ***	63.49	< .001 ***

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

SCNA layer 2: The epistemic perspective

From an epistemic perspective, the cognitive structures of leader, starter, influencer, and mediator students changed from KI-involved in the earlier phases to KC-involved in the later phases (see Figure 4). For example, leader students had different cognitive structures in the early and later phases. From Phases 1 to 4, leader students had more SKI–MKI and MKI–MKC connections, whereas from Phases 5 to 8, leader students had more SKI–SKC, SKI–MKC and SKC–MKC connections. Therefore, the leader students' cognitive structures changed from more KI-involved to more KC-involved from the earlier to the later phases. Starter students had cognitive structures between Phases 1 and 3, with strong MKI–DKI, MKI–MKC and DKI–MKC connections. They had similar structures in Phases 4 and 5, with connections between codes belonging to KI and KC. They had similar cognitive structures in Phases 7 and 8, with SKI–SKC, SKI–MKC and MKI–MKC connections. Therefore, like leader students, starter students' cognitive structures tended to move from KI-involved in the earlier phases to KC-involved in the later phases. Influencer students had strong SKI–MKI connections from Phase 1 to 4 and strong SKI–MKC connections from Phases 5 to 8. The cognitive structures of influencer students also changed from KI-involved to KC-involved from the earlier to later phases. Although there were no mediators in Phases 2 and 4, the mediator students had strong SKI–MKI connections in Phases 1 and 3 and KC-involved cognitive structures in the later phases. Thus, like influencer students, mediator students changed from KI-involved to KC-involved from the earlier to later phases.

In contrast, regular and peripheral students changed their cognitive structures from higher (e.g., DKI) to lower-level codes (e.g., SKI) (see Figure 4). Compared with Phases 1 and 2, regular students had much similar cognitive structures in the later phases, particularly in Phases 5 to 8. A closer examination revealed that regular students had strong MKI–DKI connections in the earlier phases, which changed to SKI–MKI in the later phases. Therefore, the cognitive structures of regular students weakened throughout the course. Peripheral students' cognitive structures also decreased. They had stronger SKI–MKI connections in Phases 1 to 4, which then weakened in the later phases.

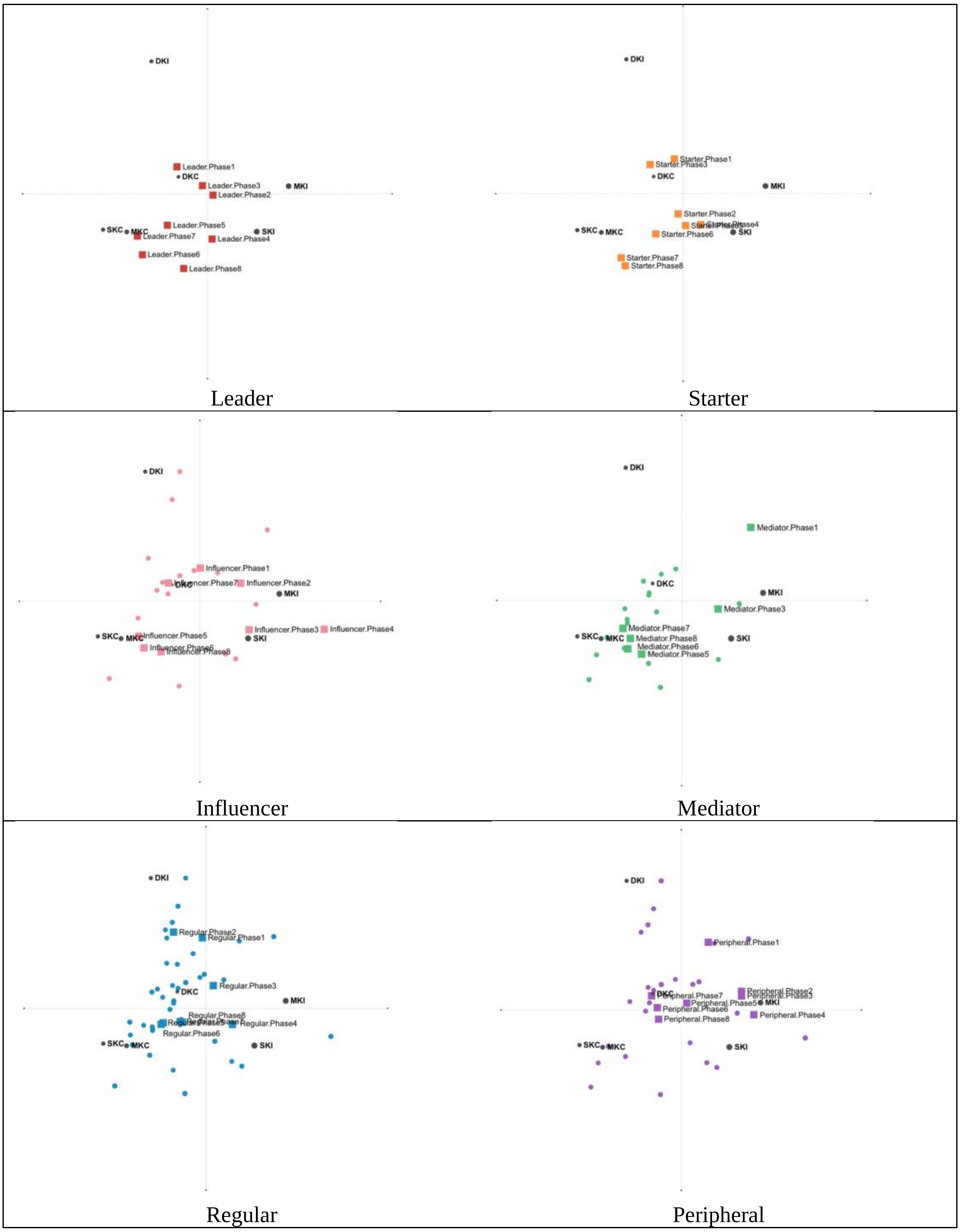


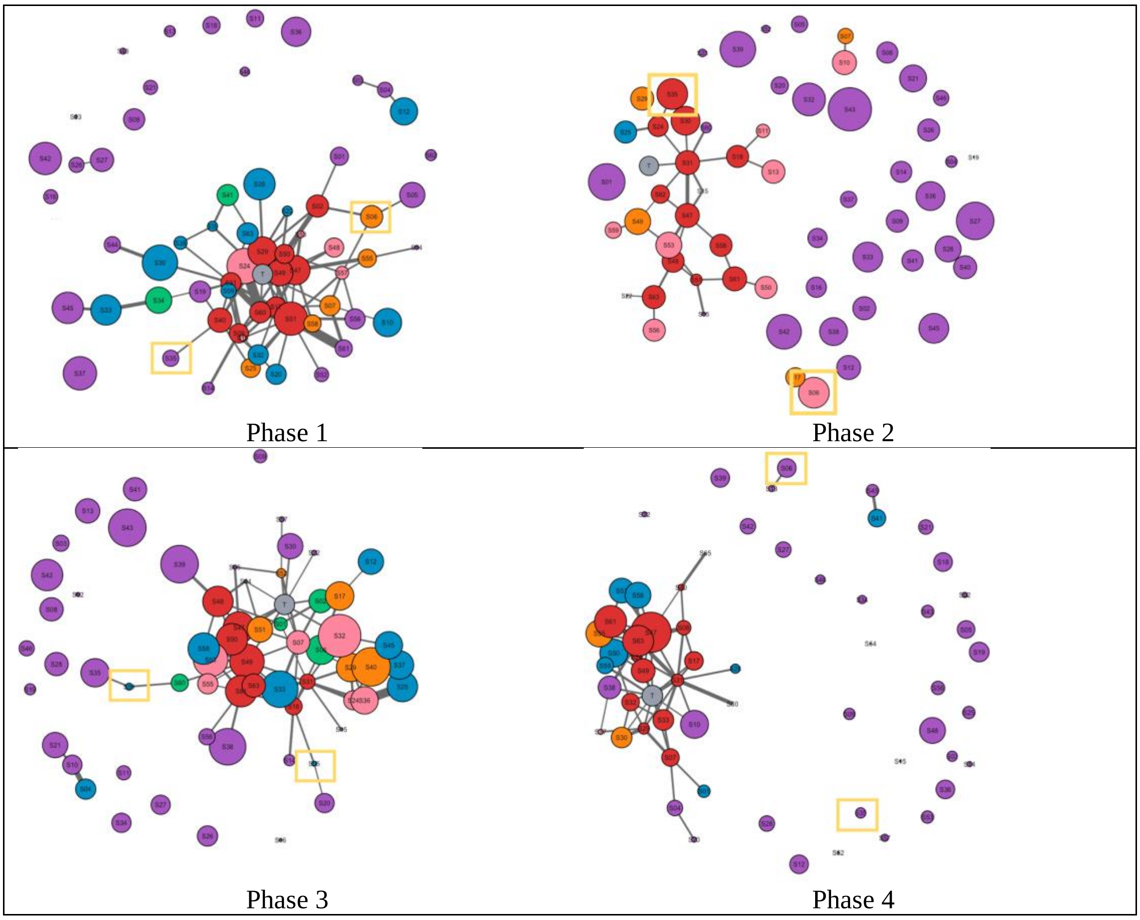
Figure 4. The ENA plots for each role across eight phases

Note. Black circles represent cognitive codes; squares represent the mean of the centroids; colour circles represent individuals. Taking starters as an example, those in Phases 7 and 8 are positioned close to each other, indicating that starters had similar cognitive structures in Phases 7 and 8.

SCNA layer 3: The micro-level perspective

From a micro-level perspective, the students showed five patterns of change in their social-cognitive engagement: *consistently active*, *consistently inactive*, *active to inactive*, *inactive to active*, and *consistently changing*:

- First, only four students maintained a socially active leader role with medium/high cognitive engagement throughout the course. For example, student S31 demonstrated a leader role from Phases 1 to 7, with weighted KI and weighted KC scores of 10.25 and 21.25, respectively, in the high range among all students (see Figure 5). S63 demonstrated a leader role from Phases 2 to 7 with weighted KI and KC scores of 14.00 and 8.25, respectively, also in the high range among the students (see Figure 5).
- Second, 14 socially inactive students consistently played an inactive peripheral role with low cognitive engagement. For example, S03, S23, S28, S64, S65, S66, S67, S68 and S69 took a peripheral role throughout the course with weighted KI and KC scores in the low range among the students (see Figure 5).
- Third, five students changed role from socially active to inactive, with a decreasing contribution to knowledge construction. For example, S07 had starter, influencer, and leader roles in the first four phases, with an average weighted KC score of 6.50, but changed to a peripheral role in the last four phases, with the weighted KC score decreasing to 4.80.
- Fourth, six students changed role from socially inactive to active with an increasing knowledge construction contribution. For example, S42 had a peripheral role in the first five phases, with a weighted KC score of 0.50, but shifted to regular, starter, and influencer roles in the last three phases, respectively, with an increased weighted KC score of 3.75. S46 held a peripheral role in the first four phases, with a weighted KC score of 0, but changed in the last four phases to regular and mediator roles with a weighted KC score increasing to 3.25.
- Finally, most students (*N* = 40) changed roles throughout the course, and their cognitive engagement levels also changed. For example, S06's role changed from starter to peripheral and then to leader, with weighted KI and KC scores first decreasing as the role became inactive and then increasing as the role became active. S35's role changed from peripheral to leader and back to peripheral, with the weighted KI and KC scores increasing and then decreasing.



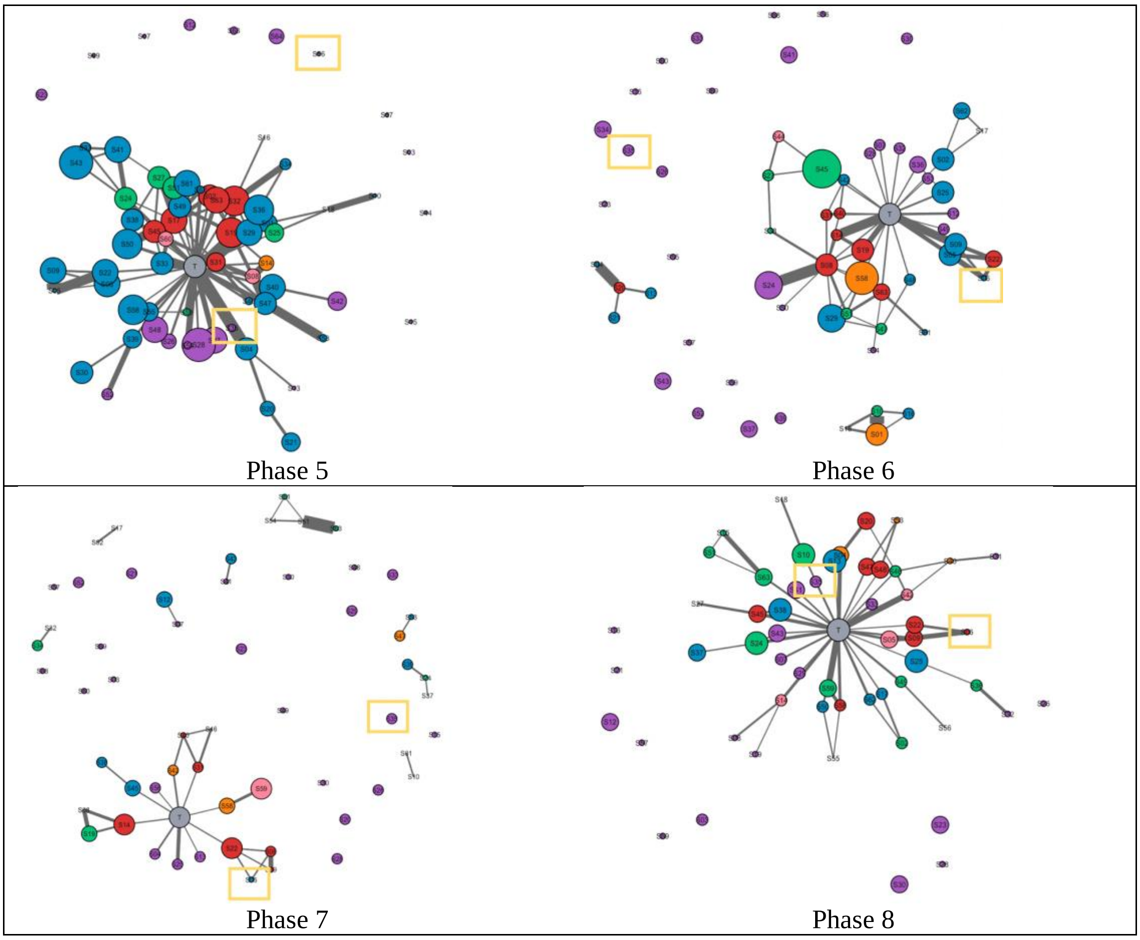


Figure 5. The social-cognitive networks of the eight phases
Note. Node size represented a student's weighted KI score, link width represented the student's weighted KC score, and node colour represented six roles (leader-red; starter-orange; influencer-pink; mediator-green; regular-blue; and peripheral-purple).

Discussion

This study proposed a three-layered SCNA supported by a multi-method approach to investigate the relationship between social and cognitive engagement in online collaborative discussions. First, at the summative level, the ANOVA results showed statistically significant differences of students' social participatory roles on levels of cognitive engagement. On average, leader students made the greatest contribution to medium- and deep-level knowledge construction (i.e., MKC and DKC). Influencer students had the highest level of overall knowledge inquiry (i.e., weighted KI). Starter students made the greatest contribution to low-level knowledge construction (SKC). Mediator students made the least contribution to all three levels of knowledge inquiry (SKI, MKI and DKI), while peripheral students made the least contribution to all three levels of knowledge construction (i.e., SKC, MKC and DKC). Moreover, *regular* students with medium levels of social interaction also had medium levels of all cognitive codes. In line with previous studies (e.g., Ouyang & Chang, 2019; Salter & Conneely, 2015; Yücel & Usluel, 2016; van Aalst, 2009), this study showed that students were unlikely to make a substantial cognitive contribution if they neither maintained continual peer interaction nor received enough peer responses. Overall, the students' social participatory roles were a critical indicator of their cognitive engagement level.

Second, at the epistemic level, students with different social participatory roles tended to show different patterns of change in their cognitive engagement. Specifically, socially active students (i.e., leaders, starters, influencers and mediators) changed from individual-level cognitive engagement (KI-involved) in the earlier phases to group-level cognitive engagement (KC-involved) in the later phases. Regular and peripheral students shifted from relatively high to relatively lower individual cognitive engagement as the course progressed. Consistent with the findings of previous research (e.g., Cesareni et al., 2015; Wise & Hsiao, 2019; J. Zhang et al., 2020), students with different social participatory roles tended to show distinct changes in cognitive engagement. Given that socially active students shifted to group-level knowledge construction, instructors should encourage students make an effort to communicate with peers and take an active role in collaborative learning. Overall, socially active students tended to change towards increasing cognitive engagement at the group level, while inactive students demonstrated decreasing cognitive engagement at the individual level.

Third, at the micro level, a large proportion of students continually changed their level of social participation and cognitive engagement throughout the discussions. For example, S35 changed from peripheral to leader and back to peripheral, first increasing and later decreasing their cognitive engagement. Unlike previous studies (Ouyang & Chang, 2019), these results suggest that the initial cognitive level established by students is probably not fixed. Active students who later reduced their peer contact probably lost opportunities to construct group-level knowledge, thereby weakening their cognitive engagement (Haya et al., 2015; Wise & Hsiao, 2019). In contrast, inactive students who started to build connections could also build reciprocity with their peers and make deep-level cognitive contributions later. Therefore, this study’s findings showed that individual students tended to change their social and cognitive engagement throughout the course. In particular, the way they built social relations critically influenced their cognitive engagement in knowledge sharing, construction and creation (Rolim et al., 2019; van Aalst, 2009; J. Zhang et al., 2020).

In addition, students’ social and cognitive engagement may be affected by their peers. For example, S42 and S46 may both have been affected by S31 (consistently active) and changed from inactive to active as the discussion progressed (see Figure 5). Similarly, S07 may have been affected by S23 (consistently inactive) and changed from active to inactive engagement. Although only a few observations in this study identified this phenomenon of mutual influence, this suggests that students had critical influences on each other during the collaborative learning process (Wise & Cui, 2018; Xie et al., 2014). Some students’ active or inactive engagement behaviour is likely to positively or negatively enhance the learning motivation of their peers, in turn increasing or decreasing their social and cognitive engagement. The results together suggest that students’ social engagement is critically connected with their cognitive contribution in online collaborative discussions. These findings have implications for enhancing collaborative learning theory, pedagogical support and learning analytics for online collaborative discussions.

Implications

Theoretical implication: Student agency

Student agency is reflected in the student’s learning intention and active learning behaviour (Bandura, 2001; Eteläpelto et al., 2013; Giddens, 1984). The results show that socially active students made deeper knowledge contributions and moved to group-level knowledge contribution as the discussion progressed. Inactive students were often on the periphery of collaborative learning, but when they increased their learning initiative and actively interacted with peers, they were also able to make in-depth group contributions. In addition, a mutual-influence phenomenon between peers was observed during this course. Active students positively influenced their peers to increase their social and cognitive engagement, while inactive students negatively influenced their peers’ engagement (Cress et al., 2013; Wise & Cui, 2018). Therefore, student agency is critical for facilitating high-quality online collaborative discussion through increasing students’ learning intentionality, autonomy and responsibility and for encouraging this agency in others through mutual influence among peers. The pedagogical support discussed below may help to develop student agency.

Pedagogical implication: Instructor facilitation

In contrast to instructor-driven learning, student-centred collaborative learning that assigns students socially active roles (e.g., leaders) can foster students’ learning intentionality, autonomy and responsibility (Ouyang et al., 2020). This study shows that socially active students tended to strengthen their group-level knowledge structure while inactive students decreased their individual-level cognitive engagement. To improve collaborative learning quality, instructors should transform their epistemic beliefs in high-level control of teaching to student-centred learning to foster student engagement. In addition, results show that the active, positive behaviour of peers can motivate students to enhance their own learning intention and participation accordingly. Therefore, instructors can assign students leadership roles to stimulate their learning engagement (e.g., Clarke et al., 2016; Ouyang et al., 2020; Ouyang & Scharber, 2017) and positively influence their peers. In addition, as the students tended to change their social and cognitive engagement over different phases of the course, instructors should pay attention to inactive students and encourage them to increase their participation. Some peripheral students did post deep-level knowledge inquiry initially but did not get enough peer responses to further construct knowledge. If high-quality comments from inactive students are ignored, they may be discouraged from further social-cognitive engagement (Ouyang & Chang, 2019). Therefore, instructors should provide pedagogical support to promote active engagement, foster mutual, positive influences and pay careful attention to students with different engagement levels.

Analytical implications: An integrated method

Echoing the innovative, integrated methods used in previous studies (e.g., Chen et al., 2017; Csanadi et al., 2018; Joksimović et al., 2018), this study proposed and applied a three-layered SCNA to examine the changes in students' cognitive and social dimensions, and the relationship between these dimensions throughout the course. The progressive development process is an important dimension of collaborative knowledge building, which occurs during students' interactive, dynamic and sustained dialogues (Chen et al., 2017). A temporal focus can reveal detailed, micro-level transitional patterns in the knowledge inquiry and construction processes, which are usually overshadowed by descriptive, summative forms of analysis and representation (Chen et al., 2017; Ouyang & Scharber, 2017; S. Zhang et al., 2017). The integrated analytical framework is beneficial for analysing collaborative learning from multiple perspectives, fostering instructors' and students' awareness of and reflection on the collaborative learning process, and enhancing collaborative learning design and facilitation (Caracelli & Greene, 1997; Chatterji, 2005; Greene, 2012). Researchers have expressed interest in further analysing the complex relationships between the social, cognitive and temporal dimensions in collaborative online discussions (Saqr et al., 2020). For example, Ouyang (2021) proposed a three-mode network analysis method to analyse the complex relationships between students, the keywords they used, and the discussions they participated in. The results indicated that compared with student interactional relations in single-mode networks, students' relations become stronger and more interactive after taking into consideration the mediating effect of knowledge construction. Overall, the proposed integrated three-layered SCNA framework can be beneficial for examining the temporality of the relationship between social and cognitive engagement in online discussions.

Conclusion

This study proposed an integrated, three-layered SCNA using a multi-method approach to examine the relationship between students' social participatory roles and their levels of cognitive engagement in online collaborative discussions. The results show that students' social participatory roles were critical indicators of their cognitive engagement level. Socially active students showed group-level cognitive engagement, while inactive students demonstrated individual-level cognitive engagement. Students tended to take consistently changing social participatory roles with fluctuating cognitive engagement. Based on these findings, this study offers implications for collaborative learning theory, pedagogical support and learning analytics. Although this study focused on a specific higher education course context in China, it demonstrates how an integrated SCNA approach can be used to examine the relationships between social and cognitive engagement from the summative, epistemic and micro-level perspectives. Future research could progress from summative to temporal analysis to reveal the nuances of the collaborative learning process. The limitations of this study include the small sample size and the participants' limited range of demographic backgrounds and learning experience. Future research should apply the analytical framework and method to a larger sample size to further validate the results and proposed implications. Overall, given the complexity of collaborative learning, researchers should use an integrated social learning analytics framework to reveal the computer-supported collaborative learning processes in finer detail from multiple perspectives.

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