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Students' Social-Cognitive Engagement in Online Discussions: An Integrated Analysis Perspective

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ABSTRACT: Grounded on constructivism, mining a complex mix of social and cognitive interrelations is key to understanding collaborative discussion in online learning. A single examination of one of these factors tends to overlook the impact of the other factor on learning. In this paper, we innovatively constructed a social-cognitive engagement setting to jointly characterize social and cognitive aspects. In the online discussion forum, this study jointly characterized students' social and cognitive aspects to investigate interactive patterns of different social-cognitive engagements and social-cognitive engagement evolution across four periods (i.e., creation, growth, maturity, and death). Multi-methods including social network analysis, content analysis, epistemic network analysis, and statistical analysis was applied in this study. The results showed that the interactive patterns of social-cognitive engagement were affected by both social network position and cognitive level. In particular, students' social network position was a vital indicator for the contributions to cognitive level of students, and cognitive level affected the related interactions to some extent. In addition, this study found a nonlinear evolutionary development of students' social-cognitive engagement. Furthermore, maturity is a critical period on which teachers should focus, as the co-occurrence of social-cognitive engagement reaches a maximum level in this period. Based on the results, this multi-perspective analysis including social and cognitive aspects can provide insightful methodological implications and practical suggestions for teachers in conducting in-depth interactive discussions.

Keywords: Social-cognitive engagement, Integrated analysis, Social network analysis (SNA), Epistemic network analysis (ENA), Knowledge building

1. Introduction

With advances in Internet technology and the large-scale application of computer-mediated communication tools, online courses have experienced tremendous growth. As the primary space for students to have discussions by posting messages, the online discussion forum provides participants with the support to interact with their peers or instructors as well as various materials for learning. Existing studies have confirmed that online discussions facilitate knowledge construction and learning engagement (Cukurova et al., 2018).

Social and cognitive aspects are two important factors that can affect academic performance in terms of parsing the interactive process of student discourse discussions (Liu & Matthews, 2005). The social aspect mainly refers to social interaction, participation, and perspective taking (Hesse et al., 2015). The cognitive aspect typically concerns knowledge construction, cognitive inquiry, and problem solving (Ouyang & Chang, 2019; Swiecki & Shaffer, 2020). According to constructivism theory (Liu & Matthews, 2005), capturing the complex interactions between the interrelated social and cognitive aspects is essential for demonstrating collaborative discussion in online learning.

Recently, several researchers have begun to attempt a joint analysis of students' social and cognitive aspects in online forums. Some studies are devoted to using multiple methods to investigate social and cognitive aspects (Peng & Xu, 2020) and their interrelationship (Tirado et al., 2015); some studies focus on the design and updating of the research framework (Ke & Xie, 2009; Wang et al., 2014); and other studies pay attention to the proposal and application of new methods (Gašević et al., 2019; Swiecki & Shaffer, 2020).

Although the above studies have provided insights into the integrated analysis of social and cognitive aspects, they have considered these aspects separately, rather than attempting to view them as a whole, which ignores the joint contribution of both to discussion-based learning. To address this issue, our research provides researchers with a novel perspective of refining students' social and cognitive discourse characteristics. Specifically, this study extracted the social and cognitive aspects of the students' characteristics separately and combined them into a new characteristic—social-cognitive engagement. Social-cognitive engagement is not a simple sum of social and cognitive characteristics, but a cross-combination that reflects both social and cognitive aspects. This cross-combination considers the intertwined impact of one aspect on the other aspect in the online discussion forum. Moreover, unlike a traditional network in which nodes represent a single attribute, the construction of social-cognitive engagement allows for the visualization of the social and cognitive aspects of nodes for a fine-grained characterization of node states and node relationships in the network.

Multi-methods were addressed to investigate the relationship between social and cognitive aspects in online discussions and interactive patterns of different social-cognitive engagements, as well as social-cognitive engagement evolution. Results can be used to uncover the evolutionary patterns of students in the learning process and help teachers better understand students' knowledge construction process in detail so that they can design reasonable teaching plans.

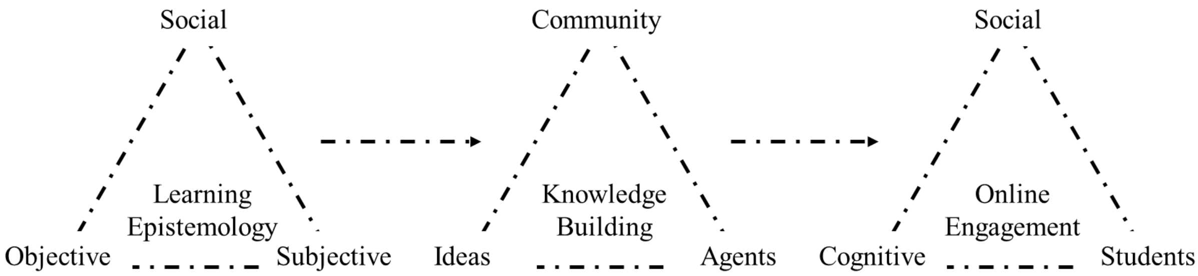
2. Theoretical framework

2.1. Theoretical foundations

Sfard (1998) explained learning as two metaphors: acquisition and participation. The acquisition metaphor demonstrates that learning can be understood through the acquisition of knowledge by individuals in their minds, while the participation metaphor suggests that learning is facilitated through social interactions between individuals in a community of practice (Teo et al., 2017). Combining the acquisition metaphor and the participation metaphor, Paavola et al. (2004) proposed a third metaphor: knowledge creation. Knowledge creation assumes that individuals engage in collaborative discussions within a community, acquiring personal knowledge and creating new knowledge that can be used in the whole community. As the main model supporting the conceptualization of knowledge creation communities, knowledge building theory makes the argument for "learning as knowledge creation" explicit and well-documented.

Knowledge building is based on the theoretical guidance of constructivism (Bereiter, 2002b; Yücel & Usluel, 2016) and can be defined as a learning process in which students generate different ideas and develop, integrate, refine, or elaborate these ideas through progressive discussion activities (Lin et al., 2014). Knowledge building involves not only students sharing their ideas but also further negotiation and discussion based on existing views and thoughts. Therefore, knowledge building stresses the social interaction process of the formation of a knowledge community.

Figure 1. Theoretical foundations of social-cognitive engagement



Hong et al. (2010) proposed that the principles guiding knowledge building could be summarized from three dimensions: ideas, agents, and community. Ideas are the building blocks of knowledge, and idea improvement is an extremely important part of knowledge building. Sometimes, ideas proposed by students may not be correct or lack reasonable explanations, but students' ideas can be changed through social interaction. This process is a major contribution to constructive learning; therefore, ideas are referred to as epistemic anchors (Bereiter, 2002a). Agents are knowledge workers who are treated as the subjects of knowledge. They obtain knowledge through sustained idea improvement and collaborative learning patterns. Agents need to assume epistemic agency and engage in the constructive use of authoritative activities. Community is a social venue for knowledge or idea interactions.

According to Descartes (Lin et al., 2014), the two most fundamental epistemological aspects concern with the object of learning, i.e., what people want to know, and the subject of learning, i.e., the learner. Between the two aspects there is also a social aspect that defines the social space in which learning takes place. The above three epistemological aspects (objective, subjective and social) constitute the conceptual framework for knowledge building. Accordingly, in this study, the three dimensions of knowledge building were mapped to the three objects of the online engagement, i.e., cognitive aspects, students, and social aspects. As shown in Figure 1. Students engage in interactions in community and generate different social characteristics indicted by the frequency, direction, and object of the interaction. In addition, their knowledge or ideas reflect different cognitive levels. Based on the constructivism, this study proposed the concept of social-cognitive engagement in an attempt to portray the learning process in online discussion. The social-cognitive engagement construction process was described in section3.4 (Data analysis).

2.2. Related literature

Social network analysis (SNA) and content analysis (CA) are commonly used to analyze the social and cognitive aspects in discussion-based learning. Recently, epistemic network analysis (ENA) has gained a lot of attention as a network analysis method to model interactions among cognitive elements (Shaffer et al., 2016). Existing literature demonstrated that ENA can be widely used in the field of learning analytics, such as thinking development (Tan et al., 2022), learning evaluation (Fougt et al., 2018) and knowledge construction (Shaffer et al., 2016). For example, Bressler et al. (2019) used ENA to examine the evolution of collaborative scientific practice and discourse of student team. Tan et al., (2022) explored the development trajectory of shared epistemic agency in collaborative learning through ENA. Overall, researchers can identify changes in students' cognitive development through comparative analysis of their cognitive networks at different periods with the help of ENA, which is conducive to guiding and nurturing students' cognitive development in actual teaching activities.

Several studies have attempted to combine SNA and CA to investigate the relationship between social and cognitive aspects (Tirado et al., 2015; Zhang et al., 2017). The coding frameworks have also been redesigned to integrate these two aspects. Social presence and cognitive presence in the community of inquiry framework (CoI) have been used to describe social and cognitive issues in learning community (Garrison et al., 2010; Popescu & Badea, 2020). An online learning interaction model was developed by Ke and Xie (2009) to evaluate the objective evidence of adults' social and cognitive engagement. The framework addresses social interactions, knowledge construction processes, and self-directed processes. Wang et al. (2014) constructed a framework for interaction and cognitive engagement in connectivist learning contexts. Operation, wayfinding, sensemaking, and innovation comprised the four levels of the framework. In addition to the updating and designing of the framework, some researchers have proposed new approaches to integrating social and cognitive aspects for analysis. The social-epistemic network signature (SENS) is a network analytics approach combining the social and cognitive perspectives of collaborative learning (Gašević et al., 2019) and the use of SENS proves that cognitive and social aspects can be modeled as networked. Also, combining SNA and ENA, Swiecki and Shaffer (2020) proposed an integrated social-epistemic network signature (iSENS).

All of the above works can be described as integrated studies on social and cognitive aspects. Nevertheless, these studies still narrate the findings separately in terms of social and cognitive aspects. For example, studies combining SNA and CA often perform correlation analysis between different network measures identified by SNA and various cognitive behaviors encoded by CA (Ouyang & Chang, 2019; Zhang et al., 2017). Coding frameworks tend to define social and cognitive aspects as two different dimensions (Ke & Xie, 2009) or artificially equate high levels of social aspect with high levels of cognitive aspect (Wang et al., 2014). Even some new methods, such as SENS, regard social and cognitive patterns as independent predictors (Swiecki & Shaffer, 2020). In summary, previous studies still separate social and cognitive aspects. Unlike previous studies, this study used SNA and CA to construct students' social-cognitive engagement, and thus explored the interactive pattern of different social-cognitive engagements. In addition, this study was interested in examining the evolution of social-cognitive engagement since learning is a dynamic evolutionary process of acquiring knowledge. Nowadays, some studies have started to focus on the dynamic evolution of online forums, such as the evolution of topic content over the duration (Peng et al., 2020; Peng & Xu, 2020) and the comparison of social networks for multi-round activity (Zhang et al., 2017). Grasping the evolutionary trends of students' dynamistic interactions can help us uncover the evolutionary patterns of students in the learning process.

2.3. Research questions

Although few studies have attempted an integrated analysis of social and cognitive aspects, the social and cognitive aspects remain fragmented, which prevents us from gaining a deeper understanding of the social and cognitive connections and their joint impact on online forums. Moreover, the interactive process of student discourse discussions cannot be understood without examining the social and cognitive aspects embodied in interactions. To tackle these issues, this study tracked students' social-cognitive engagement on online forums from the perspective of joint modeling. Specifically, this study aimed to address the following research questions:

- RQ1: What is the relationship between social and cognitive aspects in online discussions?
- RQ2: What is the pattern of students' social-cognitive engagement in online discussions?
- RQ3: How does students' social-cognitive engagement evolve at the different phases of online discussions?

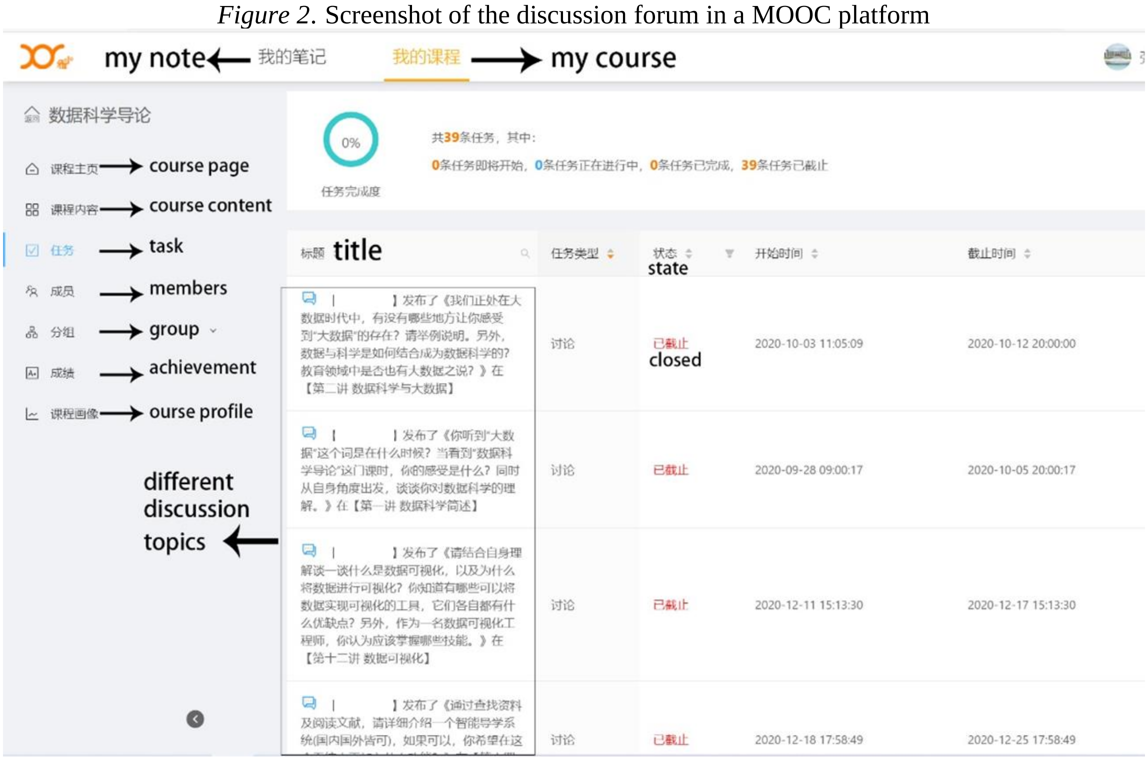
3. Methodology

3.1. Research context

The forum data were collected from a learning platform developed by National Engineering Research Center for E-Learning of Central China Normal University (CCNU). The platform in this study embeds multiple learning resources (e.g., videos, courseware, and quizzes) and learning contexts (e.g., group discussions and independent learning).

Before the course, all participants had been trained to use the platform. According to the teaching schedule, a teaching assistant posted the discussion topics on the platform every week, and students participated in the discussions. Neither the teaching assistant nor the teacher interfered with student discussions throughout the teaching activities. Fourteen discussion topics centered on the course "Introduction to Data Science" were designed to deepen these students' knowledge and understanding of data science. The discussion topics on the course content were initially delivered by the teaching assistant before the start of each class. The discussion topics covered data visualization, correlation analysis, and so on. Students could find these topics on the platform and participate in discussions, as shown in Figure 2. It is worth noting that China went through its largest online learning period in 2020 due to the COVID-19 pandemic, and this course was conducted in the first full semester after students had returned to school.

Figure 2. Screenshot of the discussion forum in a MOOC platform



3.2. Participants

The participants of this study were 35 undergraduate students who attended the course "Introduction to Data Science" at a university in Wuhan, China. All of them majored in data science and big data technology. The final course grades consisted of weighted scores from ordinary grades (70%) and final examination scores (30%).

Ordinary grades included online learning hours, attendance, collaborative activity participation, and online participation in the discussion forum. For personal reasons, one student did not participate in the final examination and was therefore excluded from the analysis related to academic performance. Final grades were normalized on a 0-100 scale (N = 34, M = 83.45, SD = 5.40). In total, 1,068 messages were posted by 35 students.

3.3. Measures

Revised Bloom's Taxonomy (RBT) was adopted as the coding scheme to operationalize cognitive behaviors to better capture students' cognitive aspects in this study. *Remember*, *understand*, and *apply* are defined as lower-order cognitive behaviors while *analyze*, *evaluate*, and *create* are defined as higher-order cognitive behaviors. In addition, *off-topic* was added to indicate the student discussions that were irrelevant to the course content, as denoted in Table 1.

Table 1. Coding scheme for cognitive behavior

Code	Categories	Example
B1	Remember	Big data is data collection that cannot be crawled, managed...
B2	Understand	The amount of data generated in the era of Big Data is incomparable to any previous period in human history ... and it will be a challenge to store such a large amount of information.
B3	Apply	I would like to know what you think are the practical problems in education and...
B4	Analyze	Artificial intelligence cannot be separated from the support of big data, because ... Deep learning is a new development direction in machine learning...
B5	Evaluate	The added system you mentioned at the end is pretty novel…and having the smart guide system simulate the idea of being a student.
B6	Create	Although Auto Tutor already implements…I would like to add a "deep personalization system" to Auto Tutor…By studying the interpersonal interactions…
B7	Off-topic	After studying, we all have a new understanding of this course, so let's do it together!

Two experienced researchers who were familiar with the RBT were invited to jointly code all 1,068 discussion messages manually. To ensure the reliability of the coding results, the kappa value was calculated, and that of the two coders was 0.76, indicating that the coded results were reliable. For other inconsistent codes, the two coders had several discussions until a consistent result was obtained.

In this study, Hyperlink-Induced Topic Search (HITS) and PageRank were provided to measure the importance of nodes in a network. PageRank is a measure for scoring the importance of nodes based on the linking relationships between them. Hub and authority are the measures of HITS. A good hub is usually linked to many other nodes and a good authority is usually linked by various hubs.

3.4. Data analysis

To address the three research questions raised, a series of methods, such as CA, SNA, ENA, and statistical methods, was applied in this study.

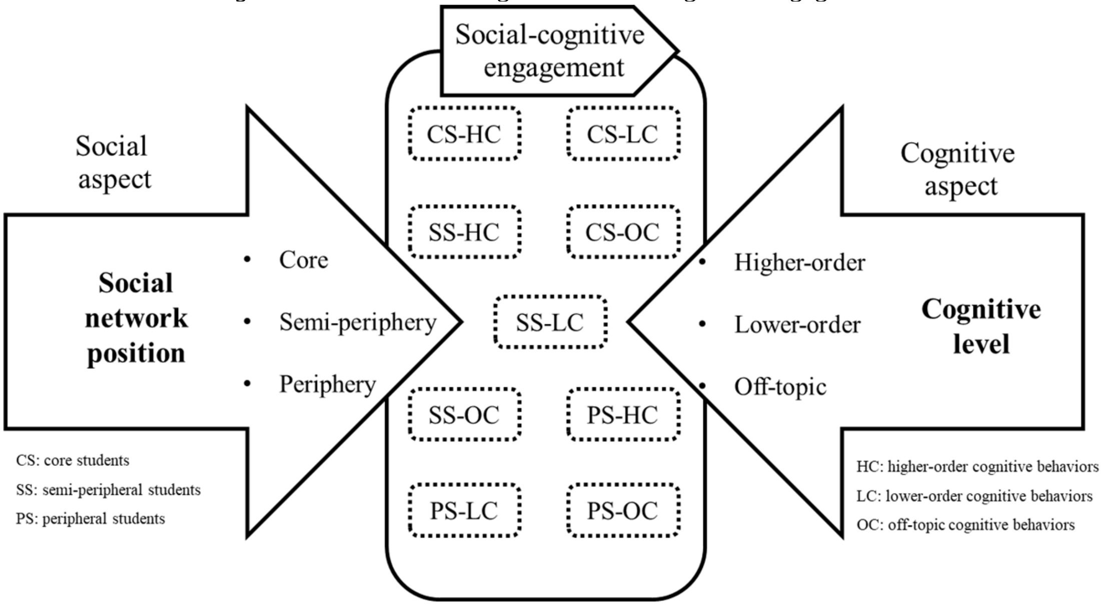
To answer the first research question, cognitive behaviors were coded, and coreness was calculated to identify students in different social network positions. Kruskal–Wallis nonparametric tests were employed to determine if there were statistically significant differences in cognitive behavior among different categories of students. When the Kruskal–Wallis tests prove a significant difference, post hoc tests (Mann–Whitney U Tests) should be performed to determine which two categories of students differ. In addition, ENA was employed to characterize the epistemic network of different categories of students.

To answer the second research question, social-cognitive engagement was constructed based on the classification of network position and cognitive level. An interactive network diagram of social-cognitive engagement was depicted to demonstrate its interactive pattern. Moreover, social network measures were calculated to examine the importance of each social-cognitive engagement in interactive networks. In addition, the Kruskal–Wallis nonparametric test and Mann–Whitney U test were used to compare the differences in academic performance in students' social-cognitive engagement.

To answer the third research question, this study divided the learning process into six phases. After referring to other similar literatures as well as conducting the actual analysis of this study, we found that when the forum was divided into six phases, on average, each student interacted with others more than 2 times per phase. This means that students will interact with more than one person or interact with the same person more than once, which can contribute to mining the evolutionary characteristics of the network as much as possible. As a measure of stability, the Jaccard coefficients (Huang et al., 2021; Zhang et al., 2016) for two sequential phases varied from 0.620 to 0.915, indicating that the network dynamics of these six phases were smooth enough and appropriate for this study. Moreover, this study employed ENA to detect the evolution of social-cognitive engagement during the discussions.

In the process of data analysis, there is one key point worth addressing: How can social-cognitive engagement be constructed? The specific analytical process was elaborated in detail as follows.

Figure 3. Construction diagram of social-cognitive engagement



In the social-cognitive engagement proposed in this study, both social and cognitive aspects should be demonstrated. On the one hand, among the two core/periphery structures proposed by Borgatti and Everett (1999), the continuous core/periphery structure uses "coreness," a quantitative indicator of network position, to determine the relative position of each node in the network and to divide the core and periphery sets of the social network. Students can be classified as core students, semi-peripheral students, or peripheral students according to their coreness. On the other hand, students' cognitive behaviors can be divided into higher-order cognitive behaviors, lower-order cognitive behaviors, and off-topic cognitive behavior. Based on social network position and cognitive level, this study constructed nine social-cognitive engagements: CS-HC, CS-LC, CS-OC, SS-HC, SS-LC, SS-OC, PS-HC, PS-LC, and PS-OC. Figure 3 illustrates the construction process. Consider the following sentence as an example: "After studying, we all have a new understanding of this course, so let's do it together!" The sentence was proposed by a student whose ID was S2. This student was defined as a core student. Additionally, the sentence was coded as off-topic. In combination, the social-cognitive engagement of this sentence was labeled CS-OC, which denotes post reflecting *off-topic* cognitive behavior proposed by a core student.

4. Results

4.1. Relationship between social and cognitive aspects in online discussions

To answer RQ1, we calculated coreness to classify students in different social network positions and coded cognitive behaviors within an online discussion, respectively. Non-parametric tests were used to identify the differences in the cognitive behavior of different categories of students, and ENA was employed to characterize the epistemic network of different categories of students.

After calculating, the correlation between the data and the idealized core/periphery structure was 0.917, indicating a good fit of the core/periphery model. The Gini coefficient was 0.641, suggesting that the coreness varied greatly among the nodes. According to the principle of classifying students with coreness greater than or equal to 0.2 as core students and those with coreness lower than or equal to 0.05 as peripheral students, the remaining students were defined as semi-peripheral students. Figure 4 shows the social network diagram of online discussion. The individual students within interactive networks were represented as nodes, and interactive relationships were visualized with lines between the nodes. In Figure 4, there are five core students (green nodes) surrounded by semi-peripheral students (orange nodes, $N = 18$) and peripheral students (purple nodes, $N = 12$).

Figure 4. The social network diagram of online discussion

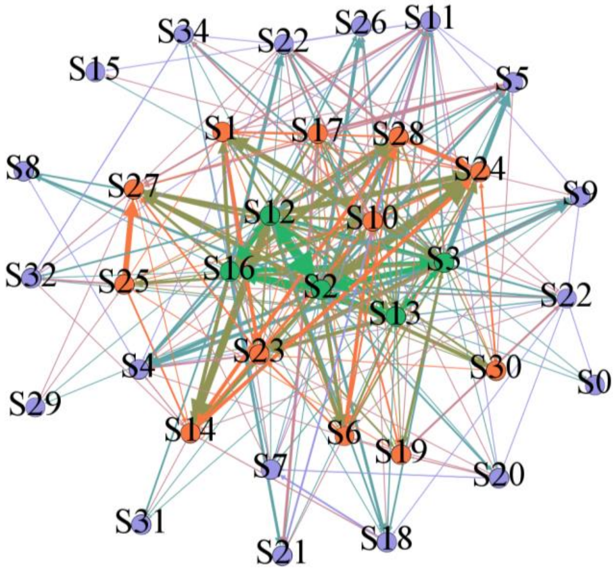


Table 2. Differences in the cognitive behaviors of different students

Type	Core students（3, n = 5）	Semi-peripheral students (2, n = 12)	peripheral students（1, n = 18）	Kruskal-Wallis Test	Post-hoc tests (Mann-Whitney U Test)
	Mean (*SD*)	Mean (*SD*)	Mean (*SD*)	*p*	
Remember	1.8（1.94）	1.58 (2.40)	0.44 (0.83)	.193	
Understand	4.6（3.01）	3.25 (1.79)	1.33 (1.29)	.005**	2>1** 3>1*
Apply	6.2（4.62）	4.08(3.20)	2.5(1.17)	.177	
analyze	8.4（3.2）	5.92(1.66)	3.89(2.33)	.006**	2>1* 3>1**
Evaluate	44.2（13.32）	8.83(5.15)	1(1.20)	.000***	2>1*** 3>1*** 3>2***
Create	3（0.63）	2.75(1.69)	1.83(1.12)	.094	3>1*
Off-topic	15.8（10.93）	7(4.20)	2.72(2.88)	.002**	2>1** 3>1**

Note. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

The proportion distributions of the three categories of students are presented in Figure 5. Core students experienced the richest cognitive behaviors and the highest percentage of higher-order cognitive behaviors (66.19%) compared with the other two categories of students (semi-peripheral students: 52.37%; peripheral students: 48.99%). Peripheral students experienced the highest percentage of lower-order cognitive behaviors (31.17%) compared with the other two categories of students (core students: 15%; semi-peripheral students: 26.68%). Semi-peripheral students experienced the highest percentage of *off-topic* behaviors (20.95%) compared with the other two categories of students (core students: 18.81%; peripheral students: 19.84%).

Kruskal–Wallis tests were conducted to compare the three categories of students in terms of each type of cognitive behavior. As presented in Table 2, four categories, *understand*, *analyze*, *evaluate*, and *off-topic*, are significantly different ($p < .01$, $p < .01$, $p < .001$, and $p < .01$, respectively).

Figure 5. The proportion distributions of cognitive behaviors in different students

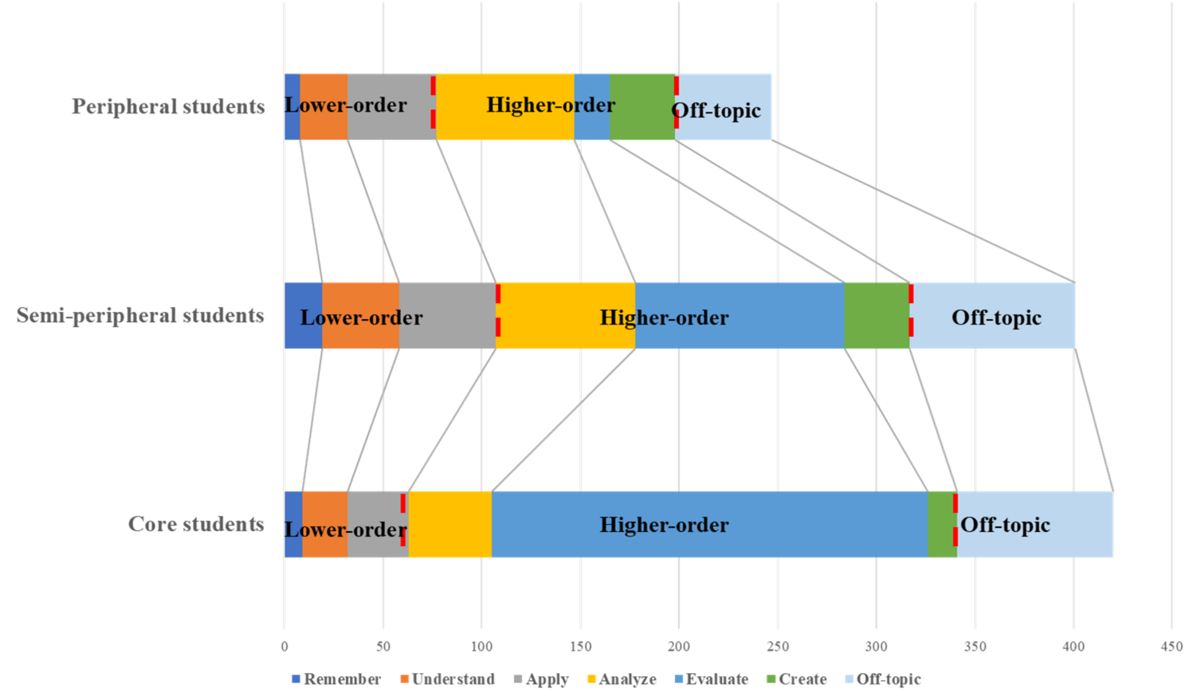
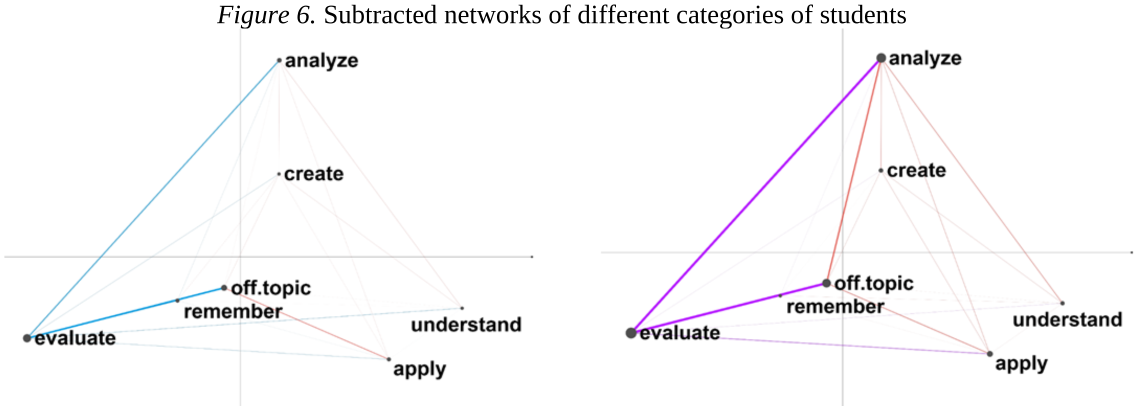
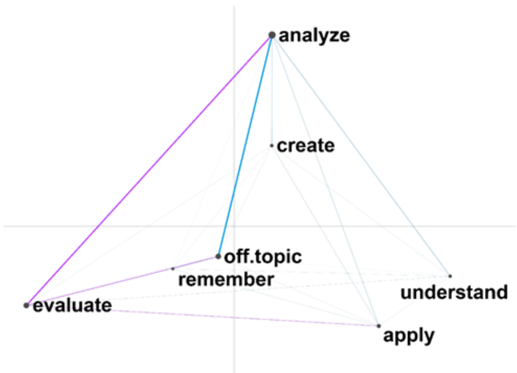


Figure 6. Subtracted networks of different categories of students



(a) Subtracted networks of core (purple) versus semi- peripheral (blue) students

(b) Subtracted networks of core versus peripheral (red) students



(c) Subtracted networks of semi- peripheral versus peripheral students

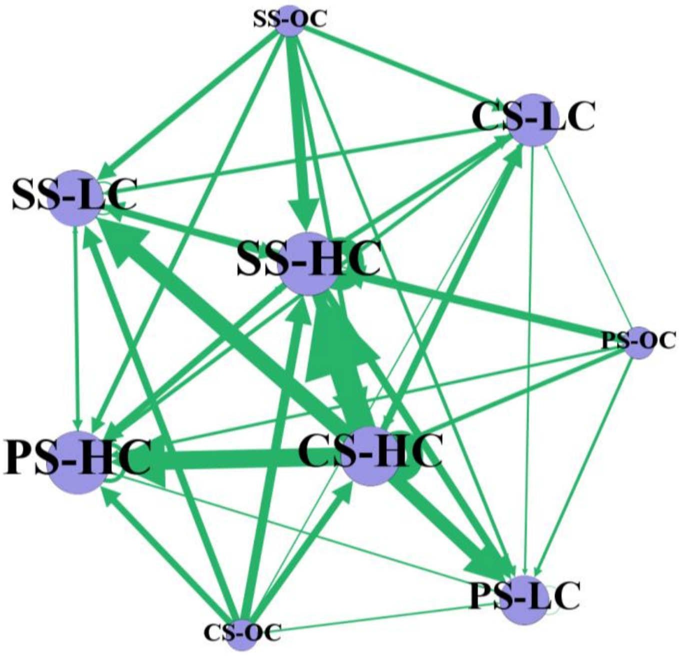
Furthermore, pairwise Mann–Whitney U Tests showed that statistical significance existed for cognitive behavior. Although *remember*, *apply*, and *create* among the three categories of students did not show significant differences (*remember*: $\chi 2$ (2, N = 35) = 3.295, p = .193; *apply*: $\chi 2$ (2, N = 35) = 3.461, p = .177; *create*: $\chi 2$ (2, N = 35) = 4.736, p = .094), Mann–Whitney U Tests revealed a significant difference between the core and peripheral students in terms of *create* (U = 18, z = −2.091, p < .05).

To explore the differences in cognitive behavior across the three types of students, a series of ENA were conducted. Figure 6 shows the subtracted networks of three types of students among different cognitive behaviors. Lower-order and *off-topic* cognitive behaviors were mainly in quadrants III and IV, and higher-order cognitive behaviors were mainly in quadrants I and III. Referring to Figure 6, compared to the other two types of students, core students had stronger connections between *analyze* and *evaluate* and between *evaluate* and *off-topic*. In contrast, significant associations were uncovered between *off-topic* and *apply* in the network for the peripheral students. In terms of the connection between *analyze* and *off-topic*, although the subtracted networks of semi-peripheral and peripheral students showed no difference, both of them were stronger than those of core students.

4.2. Interactive pattern of students' social-cognitive engagement in online discussions

To answer RQ2, we constructed social-cognitive engagement from two perspectives—social network position and cognitive level—to further describe the interactive pattern of social-cognitive engagement and to explore the relationship between social-cognitive engagement and academic performance.

Figure 7. Social-cognitive engagement interactive network



Note. Node size represents degree. The directed lines between nodes represent the frequency and direction of interactions.

After constructing social-cognitive engagement, we drew the interactive network diagram of social-cognitive engagement. Figure 7 shows a social-cognitive engagement interactive network that reveals the interaction details of the various social-cognitive engagement. It is clear that higher-order behaviors accounted for the most in terms of number and type of interactions, whereas *off-topic* cognitive behaviors involved fewer interactions. For the same level of cognitive behavior, different categories of students had all kinds of interaction characteristics. Specifically, for higher-order cognitive behavior, core students (CS-HC) were primarily involved in the response process, especially responding to semi-peripheral students. Semi-peripheral students (SS-HC) both responded to others and received responses from others. Peripheral students (PS-HC) mainly received responses from others. In addition, core and semi-peripheral students exhibited more self-interaction behaviors. For lower-order cognitive behavior, all students mainly received responses, but a small number of students in each category (CS-LC, SS-LC, and PS-LC) actively replied to others. According to the direction of interaction, all *off-topic* cognitive behaviors of students (CS-OC, PS-OC, and SS-OC) were only involved in the process of responding. In other words, students did not actively interact with content that was not related to the course.

To measure the importance of different social-cognitive engagements in interactive networks, PageRank, hub, and authority were calculated, as presented in Table 3. Regardless of the category of students, *off-topic* cognitive behaviors (CS-OC, SS-OC, and PS-OC) had the smallest PageRank value, the largest hub value, and the smallest of authority value, implying that the content reflecting *off-topic* cognitive behavior is the least important in the interaction. Higher-order cognitive behaviors (PS-HC and SS-HC) had the largest PageRank value and the largest authority value, which means that higher-order cognitive behaviors were the most important in the interaction.

Table 3. The network importance of different social-cognitive engagement

Social-cognitive engagements	PageRank	Authority	Hub
CS-OC	0.016667	0	0.397161
PS-OC	0.016667	0	0.397161
SS-OC	0.016667	0	0.397161
PS-LC	0.111358	0.407933	0.136098
CS-LC	0.111358	0.396914	0.332789
SS-LC	0.111358	0.407933	0.264842
CS-HC	0.114595	0.396914	0.332789
PS-HC	0.146969	0.419583	0.329112
SS-HC	0.146969	0.419583	0.329112

Kruskal–Wallis tests showed that social-cognitive engagements were statistically significant in terms of academic performance ($p < .001$). Pairwise Mann–Whitney U tests were performed as post-hoc analyses to find specific differences. A total of 36 comparisons were made, and a total of 27 data pairs with significant differences were found. Table 4 shows the results of data pairs with their differences. On the one hand, more achievement differences existed between social-cognitive engagement involving core and peripheral students (e.g., PS-OC, PS-LC, CS-OC, and CS-HC) and other social-cognitive engagement. On the other hand, social-cognitive engagement involving *off-topic* (e.g., PS-OC and CS-OC) differed more in terms of academic performance than did other social-cognitive engagements. Social-cognitive engagement related to semi-peripheral students did not differ from one to another related to semi-peripheral students in terms of academic performance.

Table 4. The results of data pairs related to social-cognitive engagement with differences

Sample 1	Sample 2	U	Z	*p*	Sample 1	Sample 2	U	Z	*p*
PS-OC	PS-LC	1017.5	-2.660	$.008^{**}$	PS-HC	SS-LC	1556	-9.604	$.000^{***}$
PS-OC	SS-OC	624	-5.411	$.000^{***}$	PS-HC	SS-HC	4210	-10.955	$.000^{***}$
PS-OC	SS-LC	760	-5.857	$.000^{***}$	PS-HC	CS-OC	264	-11.447	$.000^{***}$
PS-OC	SS-HC	2014	-5.75	$.000^{***}$	PS-HC	CS-LC	880	-8.601	$.000^{***}$
PS-OC	CS-OC	144	-8.406	$.000^{***}$	PS-HC	CS-HC	2772	-14.420	$.000^{***}$
PS-OC	CS-LC	480	-5.418	$.000^{***}$	SS-OC	CS-OC	1519	-4.514	$.000^{***}$
PS-OC	CS-HC	1512	-8.255	$.000^{***}$	SS-OC	CS-HC	7397	-3.621	$.000^{***}$
PS-LC	SS-OC	385	-8.446	$.000^{***}$	SS-LC	CS-OC	2317	-3.58	$.000^{***}$
PS-LC	SS-LC	482	-8.99	$.000^{***}$	SS-LC	CS-HC	9912	-3.502	$.000^{***}$
PS-LC	SS-HC	1294	-9.885	$.000^{***}$	SS-OC	CS-OC	3506	-6.957	$.000^{***}$
PS-LC	CS-OC	102	-9.886	$.000^{***}$	SS-OC	CS-HC	18631	-6.905	$.000^{***}$
PS-LC	CS-LC	340	-7.913	$.000^{***}$	CS-OC	CS-LC	1512	-3.108	$.000^{***}$
PS-LC	CS-HC	1071	-11.386	$.000^{***}$	CS-LC	CS-HC	6608	-2.538	$.011^{*}$
PS-HC	SS-OC	1324	-8.609	$.000^{***}$					

Note. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

4.3. Evolution of students' social-cognitive engagement during different phases of online discussions

To answer RQ3, we employed ENA to uncover the evolution of social-cognitive engagement during online discussions.

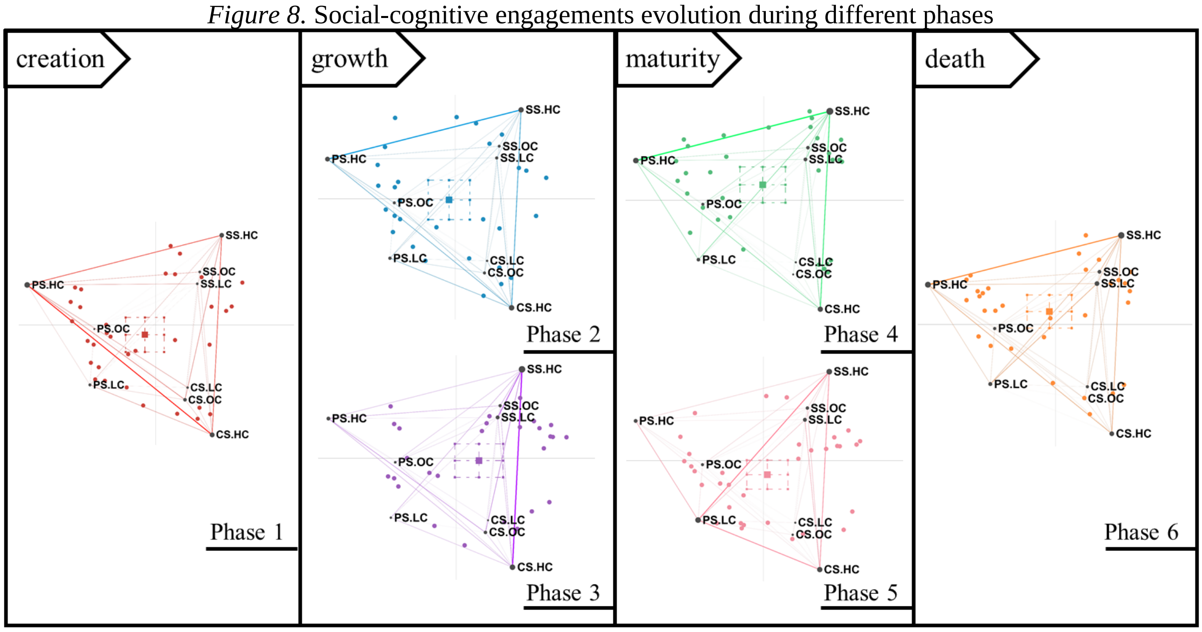
ENA characterized all the chronological networks so that the evolution of social-cognitive engagement during different phases could be compared visually and statistically. Figure 8 is the social-cognitive engagement networks for the six phases. The number of posts published in the six phases was roughly approximate. Figure 8 shows that social-cognitive engagements related to core students were mainly found in quadrant IV and that social-cognitive engagements related to semi-peripheral students were mainly found in quadrant I. Quadrants II and quadrants III were scattered with social-cognitive engagements related to peripheral students. Broadly, social-cognitive engagements related to peripheral and non-peripheral students were distinguished by the Y-axis, whereas the X-axis distinguished between social-cognitive engagements related to core students and that to semi-peripheral students. Table 5 shows the coordinates of the centroids of the six phases. The centroid takes into account the weights of the connections between cognitive elements and can be represented as a corresponding plotted point (Bressler et al., 2019). The coordinates of phases 1, 2, 4, and 6 were on the negative axis of the X-axis, which indicated that there was a relatively strong co-occurrence between the social-cognitive engagement related to peripheral students in these phases. Conversely, the coordinates of phases 1, 2, 3, and 5 were on the negative axis of the Y-axis, which indicated that there was a relatively strong connection between the social-cognitive engagement related to core students in these phases. For instance, the position of the phase 1 centroid was shown on the Cartesian coordinate system as (-0.1, -0.09). Correspondingly, there was a greater co-occurrence of social-cognitive engagement related to core students and peripheral students in phase 1.

Table 5. The coordinates of the six phases' centroids

Phases	Dimension	
	X	Y
1	-0.1	-0.09
2	-0.06	-0.01
3	0.22	-0.02
4	-0.01	0.15
5	0.04	-0.14
6	-0.06	0.13

As suggested by Iriberri and Leroy (2009), the learning process can be divided into five periods: inception, creation, growth, maturity, and death. Inception involves the design process of the online forum; during this period, the students have not yet entered the forum to participate in the interaction and therefore were not considered in this study. In Figure 8, the six phases were summarized in four periods. The changes in the co-occurrence of social-cognitive engagements indicated a learning diagram over the four periods. The findings revealed that there was a joint connection between high-order cognitive behaviors at all phases (e.g., co-occurrences between SS-HC and CS-HC).

Figure 8. Social-cognitive engagements evolution during different phases



A two-sample t-test was used to determine whether there were significant differences in the position of the phase centroid between two adjacent phases. The results indicated that phase 5 was significantly different from phases 4 (t = -2.61, p = .01) and 6 (t = -2.50, p = .02) on the Y-axis. Therefore, the development of the social-cognitive engagement network over the six phases did not follow a straight upward route but rather followed a nonlinear route: both the cognitive level and the participation of different types of students reached a relatively high level but returned to intermediate levels at phase 6, the last period, referred to death.

In the creation period, the connection between CS-HC and PS-HC (connection coefficient: 0.22) was the strongest, while some of the other connections focused on CS-HC and SS-HC (connection coefficient: 0.16), and PS-HC and SS-HC (connection coefficient: 0.17). Stronger occurrence relationships were found in the growth period for the connection between PS-HC and SS-HC (connection coefficient: 0.25) in phase 2, and CS-HC and SS-HC (connection coefficient: 0.27) in phase 3. The strongest co-occurrence of SS-HC and PS-HC (connection coefficient: 0.30) occurred in phase 4. As the death period, the distinctive co-occurrence relationships in phase 6 were PS-HC and SS-HC (connection coefficient: 0.24). As Iriberri and Leroy (2009) pointed out, discussion forums would experience poor member participation, insufficient quality of content, and weak ties between members. The fewer number of co-occurrence relationships in phase 6 was a reflection of the death.

5. Discussion

The results captured the dynamic complex interaction process in the forum at a fine-grained level that combines social and cognitive perspectives. Regarding the three research questions that range from the relationship between social and cognitive aspects to joint modeling, a detailed discussion is as follows.

5.1. Relationship between social and cognitive aspects in online discussions

With regard to the relationship between social and cognitive aspects, the results of the current study indicate that students' social network position is a vital indicator for the contributions to knowledge construction. It is clear that core students made more contributions to the overall cognitive discussion. The greatest contributions on *off-topic* were made by semi-peripheral students, and peripheral students made the greatest contribution to lower-order cognitive behaviors. Peripheral students only posted their ideas and rarely responded to the comments of others, so their contribution to the development of group knowledge construction and interactive networks was limited. The results are similar to those of previous studies. For example, regarding 20 students as the study subjects, Ouyang and Chang (2019) examined the relationships between social participatory roles and cognitive engagement levels. Results indicated that peripheral students had the lowest average scores on cognitive engagement levels. Although peripheral students were at the periphery of the social network and rarely responded to peer comments in this study, this did not mean that they rarely received comments. In this study, S26, who was a peripheral student, never responded to other students but received responses from three core students: S2, S12, and S13. Each peripheral student received a response from core students or some semi-peripheral students. The results revealed similar findings in previous studies that core students should also be reasonably well connected to peripheral students (Rombach et al., 2014). Overall, compared to other students, core students in social networks made more contributions to knowledge construction.

5.2. Interactive pattern of students' social-cognitive engagement in online discussions

With regard to the interactive pattern of social-cognitive engagement in an online discussion, the results indicated that different cognitive levels made different contributions to interaction. The different cognitive levels manifested by students in different network positions showed various interactive characteristics within the overall interactive network, but from an overall perspective, higher-order cognitive behaviors were more likely to trigger positive and more interactions than other cognitive behaviors, even the higher-order cognitive behaviors manifested by peripheral students. Take S7 as an example, S7 published a total of 14 discussion posts, 8 of which were coded as higher-order cognitive. These 8 posts received a total of 9 replies, while the other 6 non-higher-order cognitive posts did not receive replies. Consequently, in addition to the possibility that a climate of knowledge sharing and group cohesion could be formed with the help of social interaction, the development of knowledge construction also, in turn, influenced social interactions. The frequent interaction of higher-order cognitive behaviors may originate from the reflective and permanent character of online discussions. Students synthesize ideas and integrate them with their existing knowledge through continuous reflection. Precise cognitive behaviors that contain reflective meaning are the conditions for the persistence of interaction.

In addition, based on the social interactive network of these nine types of social-cognitive engagement and the calculation of their importance, social network position also affects the interactive characteristics. The social-cognitive engagement: CS-LC is a typical representative that did not exhibit self-interaction behavior. This phenomenon complements the "rich club" (Vaquero & Cebrian, 2013). Active students engage in the forum not only to build rich peer connections through persistent interactions but also to selectively respond to posts that made deep cognitive contributions. In the current study, although core students will initiate interactive connections with peripheral students, core students prefer to respond to higher-order cognitive posts made by peripheral students rather than lower-order cognitive posts and off-topic posts. Overall, different social-cognitive engagements showed different interactive characteristics, which were influenced by both social network position and cognitive level.

5.3. Evolution of students' social-cognitive engagement during different phases of online discussions

In terms of the evolution of social-cognitive engagement in online discussions, the results demonstrated nonlinear development over time. A significant higher-order cognitive tendency (e.g., CS-HC) was observed in the creation and growth periods of the online forum. This means that, when core students post higher-order cognitive posts, students' social engagement behaviors in forums will be effectively promoted, thereby improving the social network cohesion of forums. The connections among different social-cognitive engagements changed significantly with the increase in discussion activities over time, especially in phase 5. As suggested by Iriberri and Leroy (2009), a critical mass of members and member-generated content is reached at maturity, and teachers provide teaching interventions such as rewarding members or managing subgroups. At death, the forum experienced poor participation and unorganized contributions, and termination of interaction may be eminent. Discussion tasks and topics could have an impact on students' cognition, and the nonlinear development pattern could be caused by the design of topics. Overall, the four periods were characterized by the specific characterizations of the network structure of social-cognitive engagement changes in the current study.

6. Conclusions, limitations, and future research

The main contribution of this study is that the social-cognitive engagement jointly characterizes students' social and cognitive aspects, allowing us to gain a deeper understanding of knowledge construction from the perspectives of social and cognitive connections and their joint impact on online forums. The construction process provides meaningful insights for joint analysis in subsequent research. By combining SNA, CA, and ENA, the results showed that students' social network position was a vital indicator of their contributions to knowledge construction, especially core students who contributed more to knowledge construction. In addition, higher-order cognitive behaviors made more contributions to interaction. In summary, the interactive characteristics of social-cognitive engagement were affected by both social network position and cognitive level. Apart from this, the nonlinear trajectory of social-cognitive engagement uncovered its evolutionary trend. Significant changes in the connections between different social-cognitive engagements can indicate the dynamic evolution of the forum. Maturity is more informative compared to other periods, that is, there were significant differences in the position of the centroid between maturity and adjacent periods. Compared to other periods, the connection coefficient of social-cognitive engagements at maturity was not high and there was no significant co-occurrence characteristic. Based on the results, this study provides methodological implications for multi-perspective analysis and practical suggestions for teachers to improve students' social and cognitive levels.

Our study provides researchers with methodological implications from multi-perspective analysis of online forums. The combination of multiple methods, especially SNA and ENA, is a useful method to get a more comprehensive view of student engagement characteristics. Social-cognitive engagement jointly characterizes the social and cognitive aspects of students, rather than describing learning characteristics from a single social or cognitive perspective. Students were classified as core, semi-peripheral, and peripheral students according to coreness from a social perspective, and posts were defined as higher-order, lower-order, and *off-topic* cognitive behaviors from a cognitive perspective. This is an idea of joint analysis that can even be extended to other perspectives, such as sentiment in the text. Research examining sentiment evolution with different interactions is scant (Huang et al., 2021), and this study may inspire a combined cognitive, social, and emotional analysis.

In addition, our study provides practical suggestions for teachers to strengthen the development of interactive online discussions and increase students' cognitive levels. Students may provide higher-order cognitive behavior even if they are at the periphery of the social network. When students see themselves as creators of discussion-based learning, they are more inclined to actively participate in the learning process. Teachers could encourage students to participate in top-level planning, decision-making, and learning coordination activities (Ouyang & Chang, 2019) to bring peripheral students closer to the core part of the social network. In addition, to improve the quality of student interaction, teachers can provide scaffolding tools (Lin et al., 2020) and relinquish control of the forum as appropriate (Ouyang & Scharber, 2017) during the learning process. Reasonable instructional designs can be provided based on the evolutionary patterns of the network, such as rewarding mechanisms at maturity.

This study has some limitations that should be noted. First, although there are similar samples in previous studies, for example, Huang et al. (2021) used texture data of 38 students and Ouyang and Chang (2019) used discourse data of 20 learners, the generalizability of the results might be limited due to the sample data. Thus, larger samples should be incorporated in future studies to make the results more representative. Second, there may be some face-to-face interactions that might influence students' online interactions during the 14-week online discussion activities. Future research that integrates online and non-online interactions to obtain a full understanding of students' interactive behaviors is necessary. Moreover, this study constructed social-cognitive engagement based on students' network position, and other social network properties, such as social roles, can also be used. It would be of great significance to investigate students' social roles and their relationship with learning achievements in future research.

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