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Exploring a Personal Social Knowledge Network (PSKN) to aid the observation of connectivist interaction for high- and low-performing learners in connectivist massive open online courses

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Abstract

This study adds a new perspective to the observations about connectivist interaction behavior in cMOOCs by extending the notion of network building from the perspective of individuals. We explore the possibility of building a learning network named Personal Social Knowledge Network (PSKN) to support in the monitoring of learning performance and interaction in cMOOCs. The sample in this study included 284 preservice teachers and their learning lasted approximately 12 weeks. Data were primarily gathered by PSKN graphs. The results revealed a correlation between connectivist interaction measured by the PSKN (including density structure) and learning performance. The results also revealed differences in connectivist interaction behavior and patterns, indicated by PSKN (densities and structures), for high- and low-performing learners in cMOOCs. The high-performing learners show deeper knowledge interaction and social communication in addition to simple knowledge sharing and social communication. Additionally, as time passed and the PSKN of high-performing learners extended further, their interaction behavior became more complex and their role had gradually changed from "learning" to "teaching" as well as from knowledge acceptance to knowledge creation in cMOOCs.

Introduction

With the development of Web 2.0 technology and social media, learners can share, collect and edit contents with peers or friends to create knowledge. In these social spaces, learning approaches are moving away from "one-size-fits-all, content-centric models" and towards "learner-centric models" (Chatti, Jarke, & Specht, 2010, p. 74). The connectivist massive open online courses (cMOOCs) are one of these social spaces that are gaining popularity in recent years. The concept of cMOOCs is built upon the learning theory of connectivism (Siemens, 2013), which suggests that learning should be less reliant on teachers and rather more dependent on the connections that people make, both to the content and to each other (Mackness, Waite, Roberts, & Lovegrove, 2013).

Practitioner Notes

What is already known about this topic

- Connective interaction is considered an essential activity of connective learning and a way to build connections among learners in cMOOCs.
- There's a framework modeling interaction and cognitive engagement (ICE) in connectivist learning context (Wang, Chen, & Anderson, 2014), which provides clearer understanding of how connectivist learning happens from an interaction perspective in cMOOCs.
- Observing learners' connectivist interaction about their courses in cMOOCs is a key issue to understand and support the interactive behaviors of learners based on large datasets.
- Network building is an advanced perspective and approach to reveal connectivist interaction behavior during the learning processes in cMOOCs.

What this paper adds

- This study extended the notion of network building from the perspective of individual and developed a Personal Social Knowledge Network (PSKN) based on connectivism and ICE framework according to the characteristics of cMOOCs, such as knowledge sharing, collection, co-editing and creation.
- The PSKN was validated through density and structure in a real connectivist learning context by exploring how PSKN graphs differentiate connectivist interaction and learning of high- and low-performing learners in cMOOCs.
- The PSKN can help lecturers and learners see how the whole group interacts with the course, as well as the performance/engagement of individuals.

Implications for practice and/or policy

- This study can help researchers and practitioners develop a visual observation of degree and patterns of connectivist interactions among high-and low-performing learners, which can enhance the learning analysis of cMOOCs.
- The analysis method of interaction patterns and interaction behaviors among high- and low-performing learners can be used in other connectivist learning contexts to facilitate learning analysis of process-oriented MOOCs.

Though cMOOCs have brought new prospects for extending the learning opportunities to the general public, two major problems currently exist that undermine the potential impacts of cMOOCs, including the high dropout rates (Reilly & Von Munkwitz-Smith, 2013) and the high demand on instructors' workload (Mackness *et al.*, 2013). In order to address these problems, there is an increasing need for instructors to understand learners' connectivist interactions with course content and other learners (Ramesh, Goldwasser, Huang, Daume, & Getoor, 2013). Unfortunately, because of the large number of students in a single cMOOC course, it becomes nearly impossible for the instructor to monitor every student's interactions and provide personalized feedback to them. Scholars have proposed to solve these challenges using data mining and learning analytics methods, through which machine algorithms would automatically detect learning engagement and interactions in the cMOOCs environment (Wang, Anderson, & Chen, 2018). In this paper, we introduce a learning analytics approach using the Personal Social Knowledge Network (PSKN) as a means to provide assessment on students' connectivist interaction and learning in cMOOCs.

Background

cMOOCs are largely designed based on a connectivist pedagogy. Learning in cMOOCs relies on students' interactions to connect with other people and resources and to negotiate meaning with these connections. These experiences are considered a process of developing a network and connections among people, information, and digital learning artifacts within a ubiquitous network (Wang, Anderson, Chen, & Barbera, 2017, p. 684). Thus, the connectivist interactions in cMOOCs, refer not only to the interactions among learners, but also with the content and teacher; importantly, these interactions both with others and the content are vital for connection building, network formation and knowledge creation (Wang *et al.*, 2017). A variety of research studies have explored the connectivist interactions within cMOOCs environments (Downes, 2012; Siemens, 2011; Wang *et al.*, 2018). These studies generally conclude that it is critical for instructors to be able to monitor and understand their students' interaction behaviors as well as the relationship between these behaviors and students' learning outcomes (Hughes & Dobbins, 2015).

In the context of cMOOCs, learning is a connection-building and network-forming process (Siemens, 2005), therefore, the key for understanding how learning occurs in such contexts is to examine the composition of the network, which means the types of nodes as well as the relation between them. According to the connectivist perspective of learning, knowledge and learning are social in nature (eg, Polanyi, 1967; Wenger, 1998). Both human node and content node are important for connection building; and the network should demonstrate not only connections between learners but also the combination of learner-to-learner and learner-to-content interactions that leads to social relationship building as well as knowledge creation. Correspondingly, examining connection interactions from the network and connectivist perspective of learning (Downes, 2012; Siemens, 2011; Wang *et al.*, 2018) shads new lights to our understanding about learning in the cMOOCs context and also to support instructors and students to monitor their learning and behavior in cMOOCs.

Along this line of work, Wang and her colleagues focused on a typical network formed around a topic, with the aim to examine the specific technology learners used in order to support their learning and their participation patterns in connectivist learning (Wang *et al.*, 2018, p. 61). Wang *et al*'s study and their use of an overall analysis approach to examine connection interaction between groups, results in difficulties in diagnosing learners' interaction behaviors and dropout of individual learners. Therefore, analyzing the connectivist interactions based on connection-building and the network-forming process (Wang *et al.*, 2018) from the perspective of individual, is an essential component (Casquero, Ovelar, Romo, & Benito, 2015) in cMOOCs.

Besides, a variety of approaches was used to diagnose learning behavior in cMOOCs contexts, for instance, deductive analysis of qualitative data (Wang *et al.*, 2017), content analytics (Wang *et al.*, 2018) as well as social media analytics (Bozkurt *et al.*, 2016), etc. Specifically, deductive qualitative analysis is often used to establish the framework of connection interaction. For example, Wang *et al.* (2014) developed an Interaction and Cognitive Framework for cMOOCs analysis using deductive analysis. The framework includes four levels of connectivist learning interactions in cMOOCs: operation interaction, wayfinding interaction, sensemaking interaction and innovation interaction (Wang *et al.*, 2017, p. 684). Social network analysis (SNA) methods are also used to inquire how the interactions develop in cMOOCs and how researchers can examine learning behaviors by focusing on social relationships (Wang *et al.*, 2018). For example, Skrypnyk and his colleagues (2015) used a social network analysis to explore Twitter-based course interactions in a cMOOCs. Content analysis is another frequently used strategy to indirectly observe learning behaviors (Wang *et al.*, 2018). Despite these methods have great utility values in research learning in cMOOCs, they are time-consuming and labor-intensive in performing the analyses, resulting in difficulties to evaluate each learner's engagement levels and provide feedback in real time.

Interactive tools that are capable of monitoring and displaying how connectivist interactions work dynamically with both learners and content in cMOOCs would bring great advancement in educational research as well as in supporting teaching and learning in cMOOCs environments.

The present project contributes to the literature by bring a new perspective to the monitoring and diagnose of connectivist interaction behavior in cMOOCs from the perspective of network building with both learner node and human node. The project extends the individual perspective of networked learning to the network-building with both learner nodes and content nodes for analysis. The project deploys SNA and content analysis techniques in building the PSKN graphs that are used to monitor connectivist interactions and learning in cMOOCs environments.

Design and implementation of PSKN

In the connectivist learning context, knowledge and learning reside in networks (Siemens, 2005), a learner node and content node (ie, course unit node also CU node) are external connective patterns consisting of knowledge (Downes, 2012). The development of PSKN is based on the above characteristics and from the perspective of the Learning as a Network, which means that learning network is developed over time. In this setting, the learning network is the basic analysis unit. This section choose a new and typical cMOOC platform named Learning Cell System (LCS) (https://lcell.bnu.edu.cn) as for this case study, describes the design and development of a PSKN, and explores the use of PSKN graphs to differentiate connectivist interactions and learning for different learners is further introduced.

The design and development of PSKN

There are two key attributes needed to build a PSKN. One depends on what kind of nodes learners connect with (ie, content and human), or wayfinding, and the other is knowledge creation, or the degree of interaction. This section explores network building and knowledge creation from the perspective of the individual, and shows the design and development of a PSKN focus on learner node and content (course unit, CU) node (see Figure 1).

Creating the course unit—CU (lecturer-oriented)

In cMOOCs, an individual's learning approaches are oriented towards collaborative learning such as sharing, creating and making mutual connections (Bali, Crawford, Jessen, Signorelli, & Zamora, 2015). Taking into account the characteristics of the course (Bremer, 2018) and specific learning in cMOOCs (Mackness *et al*., 2013, p. 15), an individual CU is designed. Within each CU of the cMOOCs, authentic resources, application, and integration of learning activities, collaboration between peers, and development of collective knowledge becomes of great importance of learners (Margaryan, Bianco, & Littlejohn, 2015), Thus, each CU node integrates content, resources and activities. Additionally, the lecturer needs to design adequate learning activities and evaluation plans for each CU and build a default sequence for each CU to guide the learners' learning. To assessing learners engagement, the lecturer often considers a learner's sharing, discussion, collaboration and creation though diverse activities as the assessments criteria.

Social participation in activities of each CU (topic-centered)

In order to communicate with each other during learning (Downes, 2012), activity is a key factor in the connectivist learning context. To encourage sufficient activity, lecturers can design activities at different levels depending on the learning objective, and the levels of activities can be evaluated by mental efforts and cognitive engagement. Activities can include knowledge-sharing or collaborative knowledge creation. In addition, learners can search for specific CU nodes and learn socially as they collaborate with others by participating in diverse activities,

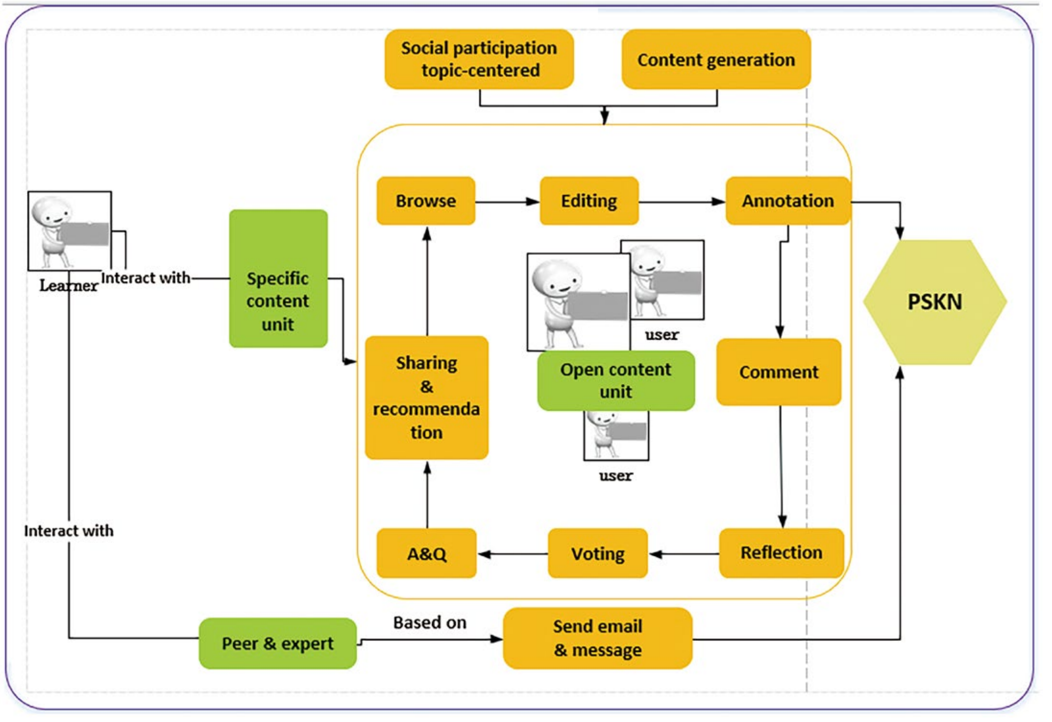

Figure 1: Design and development of a PSKN based on connectivist learning context in cMOOCs

such as browsing the CU, co-editing, annotating, commenting and reflecting, etc. Lastly, by sending an email or message to experts or friends, emotional relationships are established.

Formation of a PSKN based on connectivist learning context in cMOOCs

For a CU node, the relationship between and among CUs is based on semantic technology. Lecturers can set a passing score for each CU with the aim of measuring the learners' progress and they can add various evaluation items, such as assessing interaction and performance in learning activities and they can weigh each item differently according to importance. When a learner achieves this qualified score, the learning of this CU has been accomplished. However, when the score is lower than the qualification score, the learning process is ongoing and if the score is zero, the learner has not yet begun learning. As the learning proceeds, a PSKN is formed (see Figure 2), and learners and lecturers can observe the whole learning process visually with PSKNs over time (see Figure S1). In this sense, the PSKN displays connectivist interactions for wayfinding, sense making as well as network building, etc, the PSKN also displays the connections between CU node and CU node (connected by semantic technology), between learner node and CU node (connected based on knowledge interaction), and between learner node and learner node (friends and friends based on the social relationship and the number of CUs for common interests), so the PSKN can be used to aid the observation of behavior for different learners both from the perspective of overall and individual analysis. Individual analysis is the focus of this study, which we describe next.

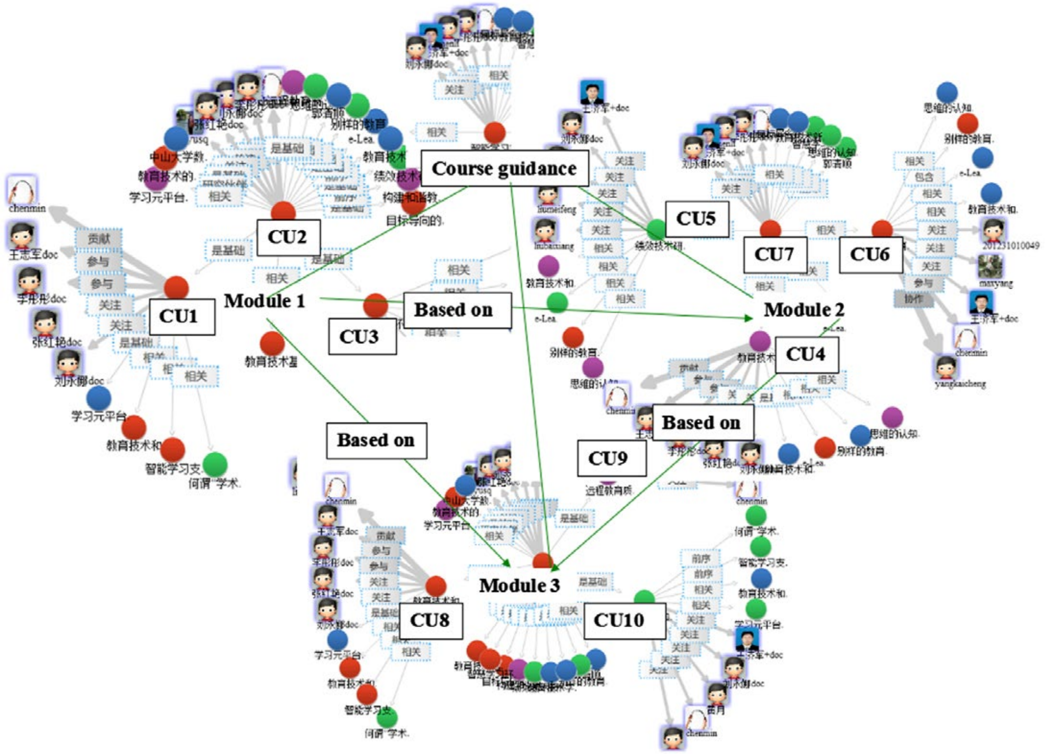

Figure 2: Overview the PSKN from the perspective of overall course structure

The implementation of PSKN in cMOOCs

In order to demonstrate the implementation of a PSKN in cMOOCs, this section first describes how to diagnose the learner's interaction behavior according to the structure and density of PSKN, and then introduces the calculation method to determine the interaction behavior data within the PSKN.

Overview of connectivist interaction from the perspective of density and structure in PSKN

As shown in Figure 3, the connectivist interaction in PSKN can be assessed both by density and structure. Network density refers to the number of nodes in a network as a proportion of total nodes possible. For example, dense networks have many nodes, while sparse ones have few. Second, the structure of the PSKN is the connectivist interaction degree (marked by CU tag and social tag) between the learners and the CU. This interaction degree is based on knowledge sharing, editing, collection, creation, etc, between CUs, as well as interaction messages (through email) between friends based on CUs. In PSKN for instance, a CU node's color represents the individual's learning interaction and engagement in this node. Green nodes represent completed units, while red nodes represent ongoing units. Also, blue nodes are created by the learner, while purple nodes represent content that is connected and saved by individuals for future activities or learning. Learners who have not started the course are not displayed in this PSKN. Additionally, friends listed in PSKN can be calculated in the same way (from the perspective of the number of CUs for common interests and social relationships). During the whole learning process, the forming of the PSKN forming becomes more dense as more CUs and more friends connect. Thus,

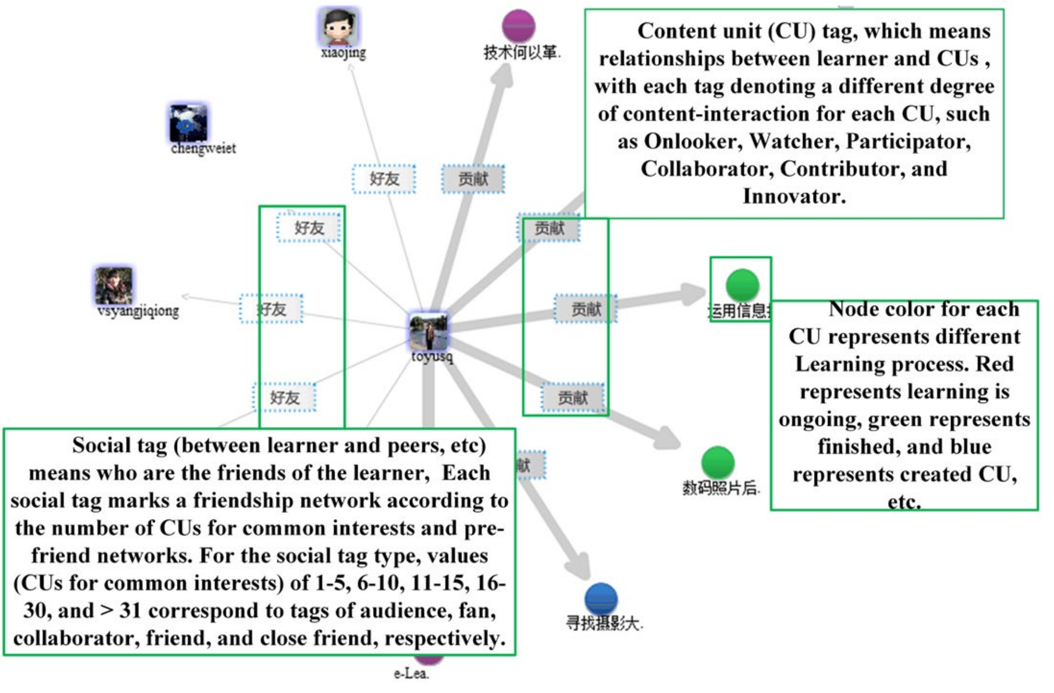

Figure 3: The connectivist interaction of PSKN from the perspective of the individual

the PSKN is dynamic and develops over time. This development can provide valuable information about interactions and behaviors of both the instructors and the learners.

Data about connectivist interaction of PSKN (density and structure) in cMOOCs

Data about connectivist interactions displayed by the PSKN can be assessed both from understanding density and structure (see Table 1). Data from the network density can be calculated using the number of CUs nodes and the number of Friends nodes, while data from the network structure refers to the number of connectivist interaction degree of CUs and the number of connectivist interaction messages (email) between friends. In the next section, we describe the calculation method for these two variables with a focus on the connectivist interaction degree of CU and friend.

Learners' collaboration, and sharing and creation of knowledge represent the different degrees of interaction that comprise the overall learning, and in the PSKN, this learner-generated knowledge is captured. In addition, learning activities were designed at different levels depending on the learning objective and degree of knowledge contribution with the aim of building new knowledge using learners' prior knowledge. Next, learning activities were evaluated to determine if any specific activity demands excessive mental effort and cognitive engagement. Considering the characteristics of the course series (Bremer, 2018) and characteristics of learning in cMOOCs (Mackness *et al.*, 2013, p. 15), PSKN combines Bloom' s revised taxonomy (Anderson *et al.*, 2000) with Wang's elements of wayfinding, sense-making, and innovation interaction (Wang *et al.*, 2014), exploring the connectivist interaction type and weighted rate for each CU node and human node in cMOOCs.

Interaction types were given different weights, based on the amount of effort of the interaction relative to other interactions as well as the degree of the knowledge contribution. For example,

Table 1: Data about connectivist interaction of PSKN (density and structure)

Items(variables)				*Label*
Density of PSKN	Number of CU (node)		Connected for learning	CU (node) color
			Finished	
			Collaborated	
			Created	
	Number of friend (node)			Human (node)
Structure of PSKN	Interaction degree of CU (node)	No action		CU tag
		Acceptance		
		Sharing		
		Refining & reflection		
		Collaboration		
		Innovation		
	Interaction degree of friend (email)			Social tag

PSKN, Personal Social Knowledge Network.

Table 2: Connectivist interaction type and weighted rate for each CU node in connectivist massive open online courses

Interaction Type (ti)	*Knowledge contribution*	*Weighted rate of each operation (wi)*	*Descriptions (behavior)*
NA	No action	0	(No Action)
W	Knowledge acceptance	1	(Watch) number of CU watched, browsed and read(reach evaluation plan, such as learning time), etc
S	Knowledge sharing	2	(Share)number of CU linked, shared and recommended, etc
R	Knowledge refining & reflection	3	(Reflect) number of CU be commented, voted, tested, reflected, revised, etc
C	Knowledge collaboration	4	(Collaboration) number of CU be co-edited , co-annotated, build-on, etc
I	Knowledge innovation	5	(Innovation)number of CU created(publish works, digital artifacts), etc

as shown in Table 2, for each CU node, “knowledge sharing” (S) interactions requires at least twice the effort and contribution than “knowledge acceptance” (W) interactions. Additionally, the “watch” (R) interaction type reflects the content and belongs to a one-to-one (many) method, whereas type “C” indicates the many-to-many method, or of collaboration and on more group-based effects. Finally, the type “knowledge innovation” (I) is defined as learners creating published works and digital artifacts through collaboration, and this interaction requires the most effort from the learners among all of the interactions.

Finally, we collected all of the interaction degrees between learner and CUs according to each learner’s contribution to the CU. For each individual, the calculation of the interaction degree used the following weighted rate:

$$\text{Connectivist interaction degree} = \text{Con}(A) = \sum_{i=1}^{10} ti * wi$$

where A represents each CU and Con(A) represents the learner's contribution value for each CU, *ti* represents the frequency of learners' content contribution, and *wi* represents the different weighted rate of each CU.

The LCS records interactions according to the types of interactions involved. In the cMOOCs when the learner interacts with a CU, the LCS will increase the correlation value based on the interaction type. For instance, when the participant creates a new CU, he/she has exhibited an I (creation) type interaction and the LCS will add 5 to the correlation value. Similarly, when the participant completes a C (collaboration) type interaction, the LCS will add 4 to the correlation value. All of a participant's interactions with a CU are recorded, and the values of each interaction (according to the above rule) are summed. Across the whole course, if a learner interacts with 10 CUs, for instance, then this individual's connectivist interaction degree the summation of each separate connectivist interaction degree. Because there are many CUs in the LCS, when constructing the participant's PSKN, it is essential to obtain the learner's related CUs and tag (see Figure S2). The LCS calculates the correlation value between the learner and CUs to obtain the list of related CUs. The CUs' creator then constructs the evaluation plan. In the plan, the creator can add different evaluation items and set different weights for the items. The creator can also set a qualified or passing score, and when the learner has achieved this score, the learner has completed the learning tasks for that CU node. Otherwise, the learning process still continues. Finally, if the score equals zero, it means that the learning has not started, the node's color represents the learner's accomplishment in that particular CU node.

Meanwhile, the human node represents the degree of social interactions and the number of friends listed in PSKN can be calculated in a similar way (from the perspective of the number of CUs for common interests and social relationship). Additionally, only individuals who are friends or close friends will be listed in the PSKN, and the number of messages (emails) between them can be recorded in the LCS.

Research questions

In this study, we use the PSKN to observe connectivist interactions for high-and low performing learners within their courses in cMOOCs. The following questions are addressed further:

1. To what extent does the connectivist interaction shown by PSKN (density and structure) correlate with their learning performance in the cMOOCs?
2. What are the differences in connectivist interaction behaviors observed by PSKN (density and structure) between high- and low-performing learners in cMOOCs?
3. How might PSKN (density and structure) indicate the different connectivist interaction patterns of high- and low-performing learners in cMOOCs?

Method

Study context and learning environment

The Learning Cell System (LCS) is a cMOOCs platform (Yu, Yang, Cheng, & Wang, 2015, p. 209) founded by Beijing Normal University, which offers open learning and training for primary and secondary school teachers. Additionally, the LCS system offers certificates and badges to learners who fulfill course requirements. As an open, generative, connected as well as social ubiquitous learning (u-Learning) environment (Yu *et al.*, 2015, p. 209), LCS provides individuals with learning content, learning activity, learning tools (such as social media, etc) and a PSKN (see Figure 4), at no cost. Also, during learning, the instructor and the learner can monitor their learning progress in real time.

The goal of our course was to allow learners to collaboratively construct a comprehensive understanding of information technology (IT) integration in classrooms. The course included three modules and ten CUs, focusing on 12 topics. The course was developed by two experts in Information and Communication Technology (ICT): a teacher with approximately 5 years of teaching experience and a tutor who lacked formal teaching experience but had extensive practical teaching skills. The two teacher-experts developed the CUs according to the course syllabus. Throughout the learning, each CU included 1–3 activities and tasks (as shown in Table 3).

Figure 5 shows a topic in module 1 asking "Why technology can innovate education? " as well as "Talk about how to use technology to enhance your professional development." The learner interface provides both the goal of this course as well as diverse activities which correspond to knowledge participation, collaboration, creation, etc. In the interface, learners connect through short-video lectures, commenting, discussing, reflecting, co-editing and creating content.

Participants

Study participants included preservice teachers who had enrolled themselves in a program that leads earning an Advanced Diploma in Information Technology in China. The preservice teachers have diverse backgrounds both in terms of their subject expertise and knowledge levels about IT. Previous studies argued that technical obstacles will at least partially frustrate learners (Li, Tang, & Zhang, 2016, p. 3). To help alleviate this concern, we gave them technology training face to face about how to navigate the LCS prior to the study.

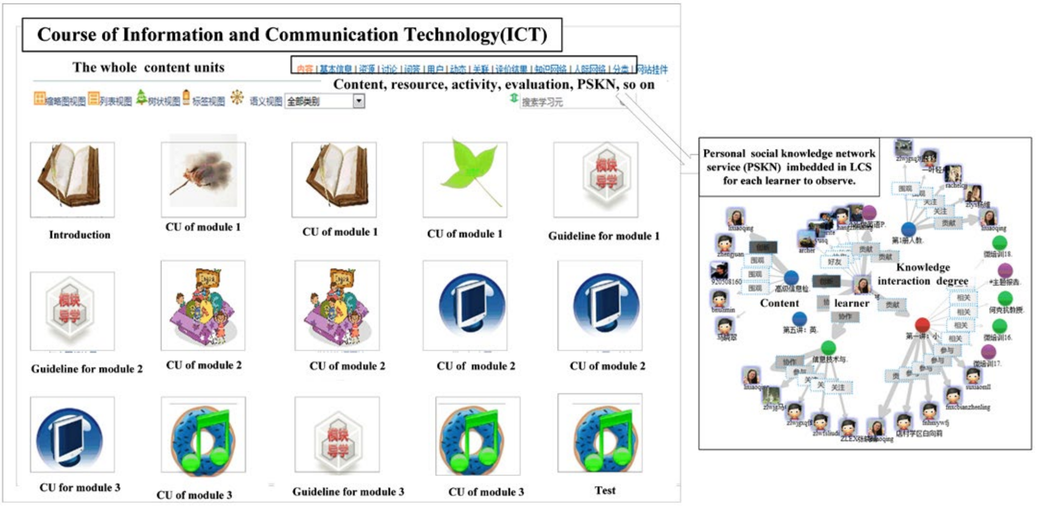

Figure 4: Basic interface of the learning system-embedded PSKN for the cMOOC

Table 3: Learning activity and interaction type for each course module

Module	*Learning activity*							
K type	*K-participation (Simple A)*			*K-collaboration (Complicate A)*				*K-creation (Innovation A)*
Activity	*Watching lectures*	*Vote*	*Test*	*Comment*	*Discussion*	*Reflection*	*Co-editing*	*Published works*
Module 1 (4 CUs)	√	√	√	√	√	√	√	
Module 2 (3 CUs)	√			√	√	√	√	√
Module 3 (3 CUs)	√		√	√	√	√	√	√

Note. K means knowledge.

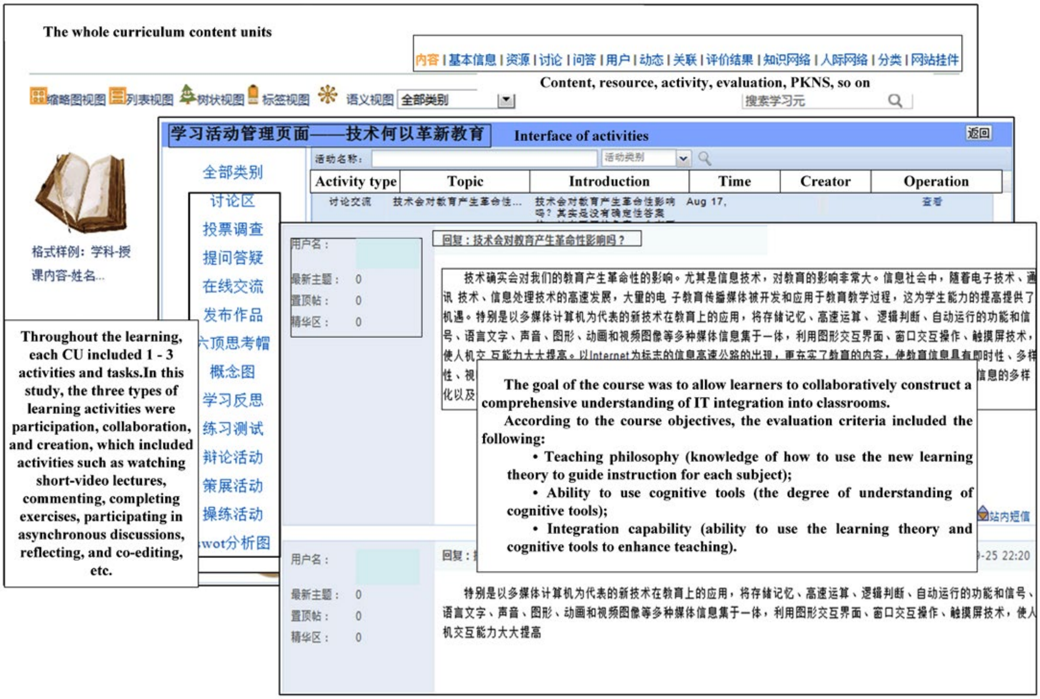

Figure 5: Screenshot of the learning interface for learners

Data collection and processing

In order to address the above-mentioned research questions, we collected data about 284 learners of the ICT course. The ICT course, begun in 2016, has attracted approximately 3119 learners. Since the course is open-ended and has attracted a large continuous enrollment, it is impossible to comprehensively analyze data from all learners generated in this course. For this study, we choose our sample according to the number of participants and activity in a given time period. The selected time period was the most active portion of participants. The initial sample is 296, and after excluding the duplicate registrants, the final sample is 284, who started their learning in 2016 which lasted 12 weeks.

In this study, the PSKN graphs and learning performance were analyzed. The data about connectivist interaction were displayed in PSKN Graphs (density and structure), which were assessed in the LCS; One interest of the study was comparing high-performing and low-performing learners. We defined high-performing learners as these in the top 50th percentile and low-performing learners as those in the bottom 50th percentile. Contrarily, other past studies have chosen to rank the high-performing learners in the above 75th percentile and low-performers ranked from the 25th percentile and below, and we choose a different approach with the aim to differentiate connectivist interactions that could enrich the analysis for all learners (Casquero *et al.*, 2015, p. 22). Further, in order to verify if learning outcomes can be predicted by connectivist interactions displayed in PSKN, the performance was examined by various statistical tests.

Before the course, we conducted a pretest to train the participants on how to use the technology provided in the course with the aim of evaluating their prior knowledge of ICT. This pretest contained 10 yes-or-no questions, 10 multiple-choice questions and 6 fill-in-the-blank questions, with a perfect score being 100. Subjects were also evaluated by the other training educators for expert validity, with $\kappa = .78 > .75$. This test measured the degree of "fit" between the tutor's and instructors' opinions. After learning, artifacts of a micro class about 5–8 minutes, requiring specific skills in knowledge creation and innovation (as a requirement for applying certificates) was used as a posttest, with a perfect score being 100. All learners' work was blind-reviewed by two experts. A kappa consistency test proposed by Cohen (1960) was conducted. The statistical results show that the consistency coefficient of two evaluators was $\kappa = .795 > .75$. This test measured the degree of "fit" between the tutor's and lecturer's opinions.

Further, in order to address how the network density and structure of PSKNs for high- and low-performing learners might indicate their performance and connectivist interaction behaviors in cMOOCs, descriptive statistics and Pearson's correlation of related variables were conducted. Next, we used stepwise regression analysis to determine whether which main variables of PSKN predicted learning performance. Further, different statistical tests about connectivist interaction behaviors and patterns displayed in PSKN between high and low performing learners were carried such as *t*-tests. Such analyses were performed using SPSS 22.0 statistical software with the significance level set at .05.

Results

Q1: To what extent does the connectivist interaction shown by PSKN (density and structure) correlate with learning performance in the cMOOCs?

To answer research question one, correlation analysis was conducted to investigate the relationship between learning performance and different attributes of the PSKN (density and structure). Table 4 shows the mean and standard deviation of learning performance, and density and structure of PSKN. For the density of PSKN, result indicated that the number of CU was significantly positively correlated with learning performance, $r(284) = .703$, $p < .01$. On the other hand, the relationship between learning performance and the number of friends (node) was positive, $r(284) = .172$, $p < .01$. These results show that friend number (based on CUs) might have the potential to serve as an effective tool for observing the learning performance. For the structure of PSKN, a statistically significant relationship was found between the learning performance and the degree of interaction of CU, $r(284) = .579$, $p < .01$; this suggests that the learners who obtained a high learning performance tended to have deeper interaction, such as sense-making interactions and innovation interactions; also, the relationship between learning performance and interaction degree of friend was positive, $r(284) = .143$, $p < .05$.

Further, a linear regression analysis was conducted to explore predictors of learning performance. A normal Q-Q plot was used to test the assumption of normality of data. This test confirmed that the learning performance was normally distributed. Multivariate linear regressions demonstrate that the number of CU can predict learning performance at the level of 49.2%, the degree of CU

Table 4: Descriptive statistics for all study variables

Variables		*M*	*SD*
	Learning performance	82.20	9.561
Density	Number of CU (node)	36.47	12.947
	Number of friend (node)	2.42	1.460
Structure	Interaction degree of CU (node)	41.96	25.802
	Interaction degree of friend (email)	.348	.917

can explain 33.3% of the variance in learning performance, however, other variables, such as friend number and friend degree indicated weak contribution of prediction (see Table 5).

Q2: What are the differences in connectivist interaction behaviors observed by PSKN (density and structure) between high- and low-performing learners in cMOOCs?

Research question one indicated, to some degree, that the PSKN could be used to help diagnose learners' performance. For research question two, we then categorized the learners into high- and low-performing groups in order to analyze differences in the connection interactions behavior between the groups.

First, an independent *t*-test was used to analyze differences between the groups on the pretest. For high-performers, the mean and standard deviation of the pretest were 42.20 and 36.046 respectively and 36.55 and 36.654 respectively, for the low-performing learners. There was no significant difference between the high- and low-performing learners in terms of prior knowledge background regarding the ICT course ($t = 1.309$, $p > .05$).

Second, we used a *t*-test to explore differences in both densities and structure for the high- and low-performing learners (see Table 6). The results confirmed that there are significant difference in both the PSKN's density and structure behaviors between high- and low-performing learners.

Third, we chose two learners (learner A and learner B) for a case study. Learner A belongs to these high-performing group, while learner B is in the low-performing group. See the PSKN ecology for the two learners (Figure 6). Learner A, who mastered six CUs, has four tags (degree of CU) marked as watcher and two tags marked as participator. As a whole, learner A' s PSKN is denser than learner B's. Further, there are more peers connected together based on knowledge creation. In addition, there is one friend that was based on the social relationship. On the other hand, learner B, who learned one CU, has one tag marked as watcher, and there are no friends connected together based on CU. Results also reveal that there are other differences between the high- and low-performing learners. High-performing learners have more preexisting friends network and a higher interest similarity among them. After learning, we randomly selected five learners in each high- and low- performing group. Mail/messages illustrated that positive emotions were displayed more obvious for these high performance ones as well as high-performing learners are more focused on higher-order thinking and complex activities.

Thus, there is a significant difference in the density and structure of PSKN between high- and low-performing learners. We can also conclude that CU (number and degree) variables predict learning performance better than human node. Further analysis was conducted to differentiate connectivist interaction pattern for high-and low-performing learners by Q3.

Table 5: Regression results on learning performance (N = 284)

Variable	β	R^2	*F value*	*Adjusted R^2 model (%)*
Network density				
CU number	.519	.494	275.045*	49.2
Friend member	.172	.03	8.642*	2.6
Network structure				
Degree of CU node	.215	.336	142.432*	33.3
Degree of friend node	1.485	.02	5.852**	1.7

$^*p < .01$, $^{**}p < .05$.

Table 6: Connectivist interaction behavior shows by PSKN between high-and low-performing learners (N = 284)

	High-performing learners (Mean, SD)	Low-performing learners (Mean, SD)	t	p
Network density				
CU number	43.85 (12.94)	29.09/7.69	11.680	.000*
Friend member	2.65/1.474	2.19/1.414	2.671	.008*
Network structure				
Degree of CU node	54.92/28.09	28.99/14.44	9.782	.000*
Degree of friend node	0.465/1.076	0.232/0.711	2.147	.033**

$^{*}p < .01$, $^{**}p < .05$.

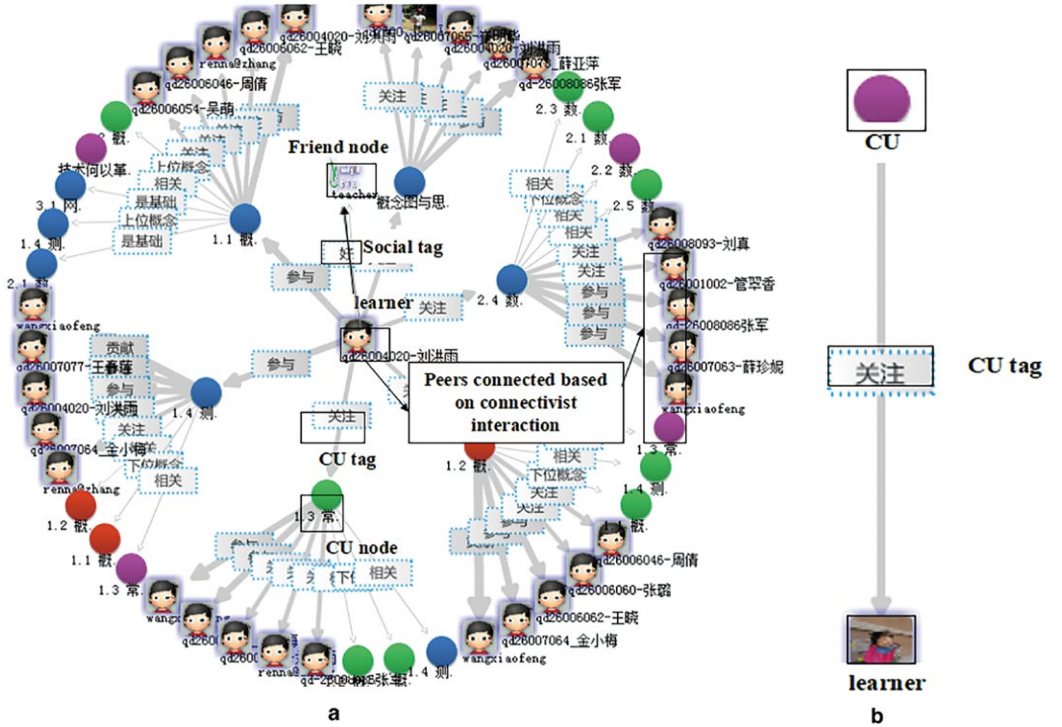

Figure 6: Screenshot of connectivist interaction comparing high- and low-performing learners in PSKN

Q3: How might the different connectivist interaction pattern be revealed by PSKN (density and structure) of high- and low-performing learners in cMOOCs?

As for the number of CU, results show there were significant differences between the high- and low-performing learners ($t = -11.680$, $p < .01$). Regarding the interaction degree of CU, we further investigated the interaction patterns indicated by the interaction frequencies between the high- and low-performing learners. We conducted a t-test to examine the differences in interaction frequencies between the high- and low-performing learners on the various knowledge levels (see Table 7). Results show there was no significant difference between the high- and low-performing learners for interaction type W ($t = -1.851$, $p > .05$). However, there was a significant difference between the high- and low-performing learners for types A ($t = 2.374$, $p < .05$), R ($t = 4.145$, $p < .01$), C ($t = 6.841$, $p < .01$) and I ($t = 3.096$, $p < .01$).

Discussion and conclusion

In the PSKN, CUs refer to how many connections are built and to what extent learners interact with CUs. Results have shown that the greater number of connections a learner built, the higher the learning performance and also greater knowledge contribution. On the other hand, the relationship and predictive ability of both the friend node and social tag is less conclusive and weaker. Casquero *et al.* (2015) argues that there are two types of interactions in technology enhanced learning, direct interaction and indirect interaction. In this study, direct interaction means that the sending or receiving message can be identified (eg, in an email) between friends, while indirect interaction refers to collaboration based on topic, sharing and reflection, etc, which contributes to the CU number and tag. The results of this study further indicate that "when public spaces based on indirect interactions are set up in online courses, learners' selection procedures for interaction are not focused on the individuals, but rather on those collaborative activities" (Casquero *et al.*, 2015, p. 26; Dawson, 2010). In summary, learning performance can be predicted by PSKN (network densities and structures) to some degree, especially by CU node and degree. The results supported the studies of Dawson (2010) and Casquero *et al.* (2015) about high-performing learners developed larger networks while low-performing learners formed small ones. We used different approaches (knowledge creation), though, to observe interactions of network building in this study, which reinforce than the PSKN approach is feasible.

For the possibility provided by PSKN to indicate differences about connectivist interaction behaviors and patterns between high-and low-performing learners, results found there is a difference in connectivist interaction behavior displayed in PSKN between high- and low-performing learners. Overall, the high-performing learners have deeper connectivist interactions with different CUs. They also have a dense PSKN, whereas low-performing learners have sparse networks in cMOOCs. Also, compared with low-performing learners, high-performing learners connected more CU nodes and social network (friends). Relatedly, another study found that high-performing students were more inclined to form social ties with other high performers, whereas low-performing students developed social ties with other low performers (Dawson, 2010). Results also found that there is no significant difference between the high- and low-performing learners in terms of

Table 7: Descriptive statistics of connectivist interaction frequency between high- and low-performing learners

Interaction type	*Mean*	*SD*	*t*	*p*
W (knowledge acceptance)			1.851	.065
High-performing learners	8.68	2.794		
Low-performing learners	8.08	2.719		
A (knowledge sharing)			2.374	.018*
High-performing learners	2.02	.221		
Low-performing learners	1.936	.361		
R(knowledge refining)			4.145	.000**
High-performing learners	5.48	8.484		
Low-performing learners	2.20	3.868		
C (knowledge collaboration)			6.841	.000**
High-performing learners	17.64	3.207		
Low-performing learners	15.04	3.176		
I (knowledge innovation)			3.096	.002**
High-performing learners	2.091	.557		
Low-performing learners	1.89	.515		

interaction type W but a significant difference between the high- and low-performing learners in terms of the participation types A, R, C and I. Therefore, in the case of high-performing learners, knowledge generation and contribution occurred frequently. Throughout the learning experience, the PSKN of high-performing learners extended further, their interaction behavior became more complex, their role had gradually changed from "learning" to "teaching," and their role changed from knowledge acceptance to knowledge creation in cMOOCs. Also, our findings reveal that the high-performing learners also had positive attitudes and interests. Additionally, interviews show that learners with high learning performance are more inclined to learn user-centric model and exhibit self-regulated learning in cMOOCs, whereas low-performing learners are more inclined to operate in an instructor-centered learning setting. One possible reason for this result is that these high-performing learners have higher levels of self-regulated learning skills.

Further, PSKN can be visualized and the individual's degree of interactive behavior can be observed throughout the entire learning process in cMOOCs. This observation-oriented assessment of PSKN overcomes barriers, reduces some of the instructor work load, and provides a way to explore the relation between connectivist interaction and performance by developing PSKN through the cMOOCs context. Therefore, PSKN can be used for learners to regulate self-directed learning in connectivist learning contexts as well as monitor and correct their learning progress. For example, the PSKN can predict learner performance by observing the learning process as a peer-assessment tool, or teachers can judge the learners' participation by observing their interaction behaviors. This may help to intervene with individuals in time before they give up completely and drop out of the course (Hughes & Dobbins, 2015). The PSKN can also be used to compare the same groups of learners throughout different stages of the course, as well as to compare different groups or learners at the same time from either the same or a different course. Additionally, PSKN can help identify wayfinding interactions, sensemaking interactions and innovation interactions (Wang *et al*., 2014). For example, the node number represents interaction of wayfinding, node color and relation tag signifies the degree of sensemaking interaction and the PSKN can be used to aid the observation of interaction behavior of different learners (innovation interaction). Lastly, the PSKN can be used to differentiate high- and low-performing learners; in this manner, instructors can then provide personalized guidance and help in connectivist learning contexts.

"Learning is connection building and network creation" (Simens, 2005) is the key of connectivism, which provides a fresh perspective about cMOOCs. This line of research is relatively new, especially the exploration of analyzing connectivist interaction and engagement of learners. Encouragingly, this study provides a clearer understanding about this issue, and this is a new and innovative approach for both network building and knowledge creation.

Results verified that PSKN can aid the observation of connectivist interaction behaviors and performance for high- and low-performing learners in cMOOCs, to some degree. The PSKN has the potential to be a useful tool to predict learning performance as well as distinguish behavior patterns for different learners in connectivist interaction context, especially for cMOOCs.

Limitations and future work

There are several limitations to this study. First, because this is an exploratory study, we only choose 284 learners as participants in a limited learning time. As time passes, ideally more participants will register in courses, and then we can observe connectivist interactions on a larger scale. Second, another limitation is that the friend node has weak correlations with learning performance.

Our follow-up research will expand the number of participants as well as explore the usefulness of the friend node for predicting learning outcomes. In this line of research, we also plan to refine the classification of learners, and explore the connectivist interaction strategies especially for low-performing learners. Meanwhile, to better understand the teachers'perceptions of PSKNs, in the future we can collect the teachers' feedback regarding perceived usefulness and perceived ease of use. Also, future work can explore the relationship between a PSKN and performances of groups, to discover how and to what degree groups and courses interact with each other. Other research should explore whether a PSKN be used for a process-oriented strategy and as a learning affordance in cMOOCs. In this manner, we plan to conduct further interventions to determine the differences between high- and low-performing learners around their group performances and social relationships, knowledge-building and interaction patterns. The PSKN can be used as a visualization tool to influence learning and collaborative knowledge-building in connectivist learning contexts. Lastly, PSKN-based massive social learning in connectivist learning contexts is also an important topic worthy of future studies.

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Statements on open data, ethics and conflict of interest

a. Original data during this research are stored in the Learning Cell System (LCS). Data can be shared with researchers for the purpose of scientific study. Interested readers should send an email to: juziduan@swu.edu.cn.
b. Data collection and use conform to the BERA ethical guidelines for educational research (www.bera.ac.uk). The data used in this study were collected anonymously.
c. No conflict of interest exits in the submission of this manuscript. I declare on behalf of my co-authors that the work described in this paper is an original research that has not been published previously and is not under consideration for publication elsewhere, in whole or in part. All the authors listed have read and approved the enclosed manuscript for publication.

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Supporting information

Additional Supporting Information may be found in the online version of this article.