

Theoretical Development of Connectivism through Innovative Application in China

Développement théorique du connectivisme à travers une application innovante en Chine

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Abstract

Connectivism, a learning theory that reveals a new learning in the Internet environment, has become a popular academic topic at the forefront of online learning. The MOOC Research Team at the Distance Education Research Centre at Beijing Normal University designed and developed the first massive open online course in China, adapting a connectivist (cMOOC) approach. Using the data collected from six offerings of the cMOOC over 3 years, the big data paradigm was used for data analysis including complex network analysis, content analysis, text mining, behaviour sequence analysis, epistemic network analysis, and statistical and econometric models. This paper summarizes the findings of the patterns of connectivist learning, including a) the basic characteristics and evolutionary patterns of complex networks, b) the characteristics and modes of knowledge production, c) the patterns of instructional interactions, and d) the relationships between “pipe” (connection) and content and between facilitators and learners. It is expected that the outcome of this study could make contributions to understanding the changes of online learning in depth and further promote the theoretical development and practical application of a connectivist approach.

Keywords: Connectivism; Innovative application; Online learning; Technology and learning

Résumé

En tant que théorie d'apprentissage qui révèle un nouvel apprentissage dans l'environnement internet, le connectivisme est devenu un sujet académique populaire à la pointe de l'apprentissage en ligne. L'équipe de recherche MOOC du Centre de Recherche sur l'Enseignement à Distance de l'Université Normale de Pékin a conçu et développé le premier cours en ligne ouvert et massif, adaptant une approche connectiviste (cMOOC) en Chine. À partir des données recueillies dans le cadre de six offres du cMOOC sur une période de trois ans, le paradigme du big data a été utilisé pour l'analyse des données, y compris l'analyse de réseaux complexes, l'analyse de contenu, l'exploration de textes, l'analyse de séquences de comportements, l'analyse de réseaux épistémiques

et les modèles statistiques et économétriques. Cet article résume les résultats des modèles d'apprentissage connectiviste, incluant a) les caractéristiques de base et les modèles d'évolution des réseaux complexes, b) les caractéristiques et les modes de production de connaissances, c) les modèles d'interactions pédagogiques, et d) les relations entre le tuyau d'information et le contenu et entre les facilitateurs et les apprenants. On s'attend à ce que les résultats de cette étude puissent contribuer à une compréhension approfondie des changements de l'apprentissage en ligne et promouvoir davantage le développement théorique et l'application pratique d'une approche connectiviste.

Mots-clés : Connectivisme ; application innovante ; apprentissage en ligne ; technologie et apprentissage

Introduction

In 2005, facing the challenge to human learning from the overload of available knowledge in the Internet era, George Siemens and Stephen Downes proposed connectivist theory, offering a new perspective of interpreting learning and knowledge generation. The connectivist theory argues that knowledge is a dynamic, invisible, and generative network phenomenon (Downes, 2005). According to this theory, possession and grasp of knowledge is not the goal of learning; instead, learning is a process of continuously building connections and developing networks (Siemens, 2005). Together, the interactions among three levels of networks (the individual level, group level, and collective level) and among three types of networks (cognitive neural networks, concept networks, and social networks) have enhanced learning development and knowledge innovation. Once proposed, connectivist theory drew much attention from researchers and practitioners in China and abroad. As of November 2021, the paper that first explained the connectivist theory, "Connectivism: A Learning Theory for the Digital Age," had been cited 4,687 times. Since 2010, research on connectivism has grown in waves. In 2011, The *International Review of Research in Open & Distance Learning* journal published a special issue entitled "Connectivism: Design and Delivery of Social Networked Learning" to encourage researchers across the world to engage in explorations of connectivism. In terms of practice, beginning in 2008, the team of George Siemens and Stephen Downes developed a series of online courses guided by connectivism, providing rich experiences for the design and development of cMOOCs later in China and abroad.

In October 2018, the Distance Education Research Centre MOOC Research Team designed and developed the first cMOOC in China, named "Internet plus Education: Dialogue between Theory and Practice." As of August 2021, six offerings of the cMOOC were delivered, which promoted the localization of connectivism in China and provided abundant data to support further exploration of the patterns of connectivist learning. Based on the big data paradigm, the data collected from users on the e-learning platform and through questionnaire survey and interview was analyzed including complex network analysis, content analysis, text mining, behaviour sequence analysis, epistemic network analysis, and statistical and econometric models. The outcomes of the research were published in several Chinese academic journals relating to four aspects: the patterns of complex networks, patterns of knowledge generation, patterns of instructional interactions, and

two important relationships between pipe and content and between facilitators and learners in connectivist learning. It is hoped that, by detailing these findings over the past 3 years, this paper will provide theoretical support to practitioners in online learning and prompt researchers to rethink the connectivist theory, and together with these stakeholders to promote the application and development of connectivism.

Methodology

Participants

Over the past 3 years, the MOOC research team designed and developed the cMOOC, *Internet plus Education: Dialogue between Theory and Practice*, and carried out a series of studies based on six offerings of the cMOOC. The number of participants in each of the six offerings are summarized in Table 1.

Table 1 shows that a total of 5,426 people participated in the six cMOOC courses. Among them, 36.07% were male and 63.93% were female. The age ranged between 19 and 65 years with an average age of 31 years, and the students attended from 34 provincial-level administrative regions in China.

It was also found that the majority of learners were willing to share their ideas and experiences, including frontline teachers (about 36.09%), educational managers (about 8.61%), industry practitioners (about 11.60%), and students (about 39.22%).

Table 1

Number of the Participants in Each cMOOC Course Offering

Round	Students
cMOOC1.0	602
cMOOC2.0	1,445
cMOOC3.0	876
cMOOC4.0	1,660
cMOOC5.0	595
cMOOC6.0	248
Total	5,426

Curriculum Design and Arrangement

The *Internet plus Education: Dialogue between Theory and Practice* cMOOC is an open, distributed, learner-defined, generative community course. It is the first cMOOC developed in

China using connectivism after a series of cMOOCs opened to the public by George Siemens and Stephen Downes. In this cMOOC there were five complex topics in the field of "Internet plus education," which included the philosophy of the Internet plus education, the fusion of online and offline learning spaces, co-construction and sharing of social education resources, consumption-driven education supply-side reform, and the use of an accurate and efficient education management model. Learners with different expertise and experiences have made active contributions in the courses, carried out multi-modal interaction and discussion around complex practical problems, promoted complex problem-solving and knowledge creation through the aggregation of collective wisdom, and built an open learning community in the field of Internet education. On October 17, 2018, the first cMOOC was offered, and by August 2021, the course had run six times. Each cMOOC ran for about 12 weeks, with the course cycle upgrading, the course content, activities, platform, and operation mode continued to evolve iteratively. The basic information collected from the six cMOOCs is shown in Table 2.

Table 2*Basic Information of the Six cMOOC Course Offerings*

	Course dates	Orientation and characteristics	Content generation
cMOOC1.0	2018.10.17 - 2019.01.05	Case analysis and theoretical discussion	14 online or offline seminars, 66 daily posts, 10,568 interactive behaviours, 310 blogs, 431 cases and resources
cMOOC2.0	2019.03.12 - 2019.06.11	Explore patterns, share tools, and create solutions	10 online or offline seminars, 5 tool-sharing activities, 23 weekly posts, 54 forum topics, 1,042 articles
cMOOC3.0	2019.10.14 - 2020.01.05	Emphasize connectivity and collaboration to solve real problems	5 online seminars, 18 theme learning videos (4h 23min), 12 weekly posts, 54 forum topics, 13 collaborative groups
cMOOC4.0	2020.03.16 - 2020.06.07	Based on the epidemic practice, focus on real problems	7 online seminars, 12 weekly posts, 46 forum topics, 12 collaborative groups, 1006 articles, 3514 comments
cMOOC5.0	2020.10.12 - 2021.01.03	Optimize activity design, enrich learning support, and emphasize collaboration	9 online seminars, 11 weekly posts, 61 forum topics, 12 collaborative groups, 393 articles, 828 comments.
cMOOC6.0	2021.06.01 - 2021.08.22	Simplify content and focus on practical issues	3 online seminars, 11 weekly posts, 11 forum topics, 5 collaborative groups, 205 articles, 563 comments

Data Analysis

In the past 3 years, based on the practice of six cMOOC offerings, the research team collected data from the e-learning platform and from questionnaires and interviews, followed by a data-intensive research paradigm. The team carried out a systematic study using a variety of data analysis methods, such as complex network analysis, content analysis, text mining (like Word2vec and the Latent Dirichlet Allocation), lag sequence analysis, epistemic network analysis, and statistical and econometric models. A series of research findings were produced and published in Chinese academic journals related to four aspects, including patterns of complex networks, patterns of knowledge generation, patterns of instructional interactions, and the two important relationships between pipe and content and between facilitators and learners in connectivist learning.

Results

Patterns of Complex Networks in Connectivist Learning

Connectivist learning depends on an open and connective network environment. The formation and development of networks are essential characteristics of learning (Siemens, 2005), with each learner situated in a complex learning network. Since the beginning of 2000, research on social networks has grown exponentially (Porter & Woo, 2015). An increasing amount of research has applied complex network analysis to explore patterns in connectivist learning, with a major focus on the structures and characteristics of social networks. The social network is usually defined as a complex network structure made up of individuals and their social relations. The complexity of social networks is mainly reflected in the diverse characteristics of network connections, the dynamic evolution of network structures, and the influences that networks exert on each other (Huang & Tan, 2017). The research team attempted to reveal the patterns of complex networks in connectivist learning from two perspectives: the basic structural characteristics and the evolutionary patterns.

Basic Characteristics of Complex Networks in Connectivist Learning

The static overall, local, and individual network indicators were employed to reveal complex networks' basic structural characteristics in connectivist learning: overall indicators include the size, topology, density, diameter, average clustering coefficient, and average path length. Existing research typically uses the overall indicators to measure social networks' cohesion and degree distribution (Tirado et al., 2017; Zhou, 2010). Local analysis indicators are usually employed to analyze the structures of groups in networks (Skrypnik et al., 2014), including the largest connected region, elements, factions, and block models. Individual indicators are usually used for examining nodes' positions and roles in network, including such indicators as degree, closeness centrality, betweenness centrality, eigenvector centrality, k-shell, structural holes, and middleman. As show in Table 3, different individual indicators can measure individuals' status and roles in networks from different perspectives (Xu & Du, 2021). Usually, researchers select two or three indicators to measure individuals' behavioural tendencies in networks (Tawfik et al., 2017).

Table 3*The Evaluation Framework of Individual Status in Social Networks in cMOOC*

Indicators	Its representational significance in learning
In-degree	One's popularity during interaction
Out-degree	One's initiative during interaction
Betweenness centrality	One's power to control information flow
Closeness centrality	One's closeness to other learners
Eigenvector centrality	One's closeness to other important learners
K-shell	One's power to information spreading

Note. From “What participation types of learners are there in connectivist learning: an analysis of a cMOOC from the dual perspectives of social network and concept network characteristics,” by Xu and Du, 2021, *Interactive Learning Environments*, p.3.

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There were two findings on the basic characteristics of complex networks in the study. First, there were four characteristics of social networks in connectivist learning: self-organized, multi-cored, modularized, and small-world effect. By analysing the clustering subgroups in the cMOOC1.0 social network and calculating indicators of network status by Ucinet (a tool for social network analysis), it was found that learners self-organized into multiple subgroups, the social network demonstrated a multi-centre characteristic, and some core learners whose status was equal to or higher than that of facilitators had emerged (Guo et al., 2020; H. M. Wang & Chen, 2019). Using the cMOOC2.0 data to retest the characteristic of self-organization, it was found that after deleting the facilitators' nodes, the modularity index of the social network increased from 0.202 to 0.252, indicating that in the absence of facilitators, learners will create their own communities, although groups still exist by self-organization (Yu et al., 2020). Several analyses also indicate that the diameter of the social network formed under the cMOOC is less than 6, the average path length is approximately 2.5, and the average clustering coefficient is approximately 0.32. These values show that there is a small-world effect and a compact structure in the social network; because of this, information propagation in it is fast (Guo et al., 2020; Xu, 2020; Yang et al., 2020).

Second, using the cMOOC2.0 data, the research team further tested the influences of special nodes on the structure of the collective network. Comparing the network structure parameters before and after the bridge learners (acting as a mediator to facilitate connections between other learners) were deleted, it was found that after deleting bridge learners, the network's average degree, density, average clustering coefficient, and modularity index all decreased significantly, while the average path length increased. The average value of the nodes' degrees in the network saw a significant decrease as well. These findings indicate that the bridge learners can influence the

others' number of connections and increase the level of modularity in the network (Yu et al., 2020).

Evolutional Pattern of Complex Networks in Connectivist Learning

By converting the dynamic network into several static networks at certain time intervals, calculating and analysing the changes of indicators over time, and using descriptive statistics analysis, the evolutional pattern of complex networks in connectivist learning can be revealed. The time intervals, based on the week, learning topic, and important activity nodes, were chosen according to the purpose of different studies. The research team gave attention to the evolution of the whole network structure and the tendency of individual connections. The evolutional analysis of the whole network is supported by indicators such as the network density, average path length, average clustering coefficient, and average degree, while the degree correlation was used to measure individuals' tendency to develop and maintain connections.

It was found that there was the phenomenon of class differentiation, or “the rich getting richer” in connectivist social networks, based on our analysis of the evolution of the degree distribution in the cMOOC2.0 network. This shows that as the course progresses, some learners become stable active learners at the centre of the network and become the ones with whom most learners would like to actively interact. According to the correlation analysis of learners' interactions (behaviours of sending and receiving messages) during a given week and their degrees (number of connected learners) in the previous week, it appears that the frequency of learner's interaction behaviour has a moderately strong correlation with their degrees in the previous week. In other words, the greater the degrees of the learners, the more active they will be in later connections and the more likely it is that they will be connected. This finding indirectly suggests that learners tend to choose others with greater degrees (learners who make more connections) when building connections (Xiong, 2020).

Meanwhile, it was also found that the structures of connectivist social networks were increasingly compact, and the speed of information propagation was accelerating. The learning topic was used to set time intervals and analyze the evolutionary trend of the cMOOC1.0 social network parameters over time. According to the results, although the number of participants differed, the networks' average degree (from 9.797 to 11.243), density (from 0.0811 to 0.113), and average clustering coefficient (from 0.281 to 0.448) showed growing trends, while the network diameter (from 8 to 5) and average path length (from 2.794 to 2.399) gradually decreased. In other words, as the course progresses, learners slowly adapt to this type of learning and gain the ability to develop more connections with peers. In comparison with the social networks formed under Weibo (a social platform in China, of which the average path length is 3.09 and the average clustering coefficient is 0.21) and the Renren Web (another social platform in China, of which the average path length is 3.48 and the average clustering coefficient is 0.20), social interactions between cMOOC learners are closer and more frequent, and the speed of information propagation gradually increases (Xu, 2020).

Patterns of Knowledge Generation in Connectivist Learning

In his book *Knowing Knowledge*, George Siemens (2006, p. 17) divided knowledge into hard knowledge and soft knowledge based on the speed of change. In the Internet environment, the

amount of information is dramatically growing, the information decay cycle is becoming shorter, the pace of information renewal is accelerating, and there is increasingly more soft knowledge. Soft knowledge includes large quantities of instant and practical experiences that are absent from books or hard knowledge. As a new type of learning, connectivist learning is exactly oriented toward soft knowledge. It not only explains the new learning phenomena on the Internet, but also reveals the new connotation of networked knowledge and new ways of knowledge generation.

New Characteristics of Knowledge in Connectivist Learning

Siemens and Downes offered a series of opinions on the new connotation and characteristics of knowledge in connectivist learning, including the following: a) Knowledge is a network phenomenon (Downes, 2005). The organizational form of knowledge uses dynamic networks, no matter whether the knowledge exists in individuals' brains or in society (Siemens, 2006, p. 2); b) Knowledge in networks is dynamic (or mobile), invisible, and generative; and c) Contents, contexts, and pipes formulate the meaning of knowledge. Contents start the circulation of knowledge, contexts make knowledge meaningful, and pipes make it connected, transmitted, and accessible (Siemens, 2006, p. 122). These comments highlight that knowledge in connectivist learning has new characteristics, and there is a need to develop an in-depth understanding of new knowledge based on data and practical context. On one hand, based on experience delivering the cMOOCs, the research team strived to enrich the understanding of the new knowledge in connectivist learning and developed a theoretical model of networked knowledge. On the other hand, diverse methods were used to reveal the characteristics of cMOOC knowledge. For example, the word2vec algorithm was used to output word vectors (Li et al., 2020), and the latent Dirichlet allocation method was employed to mine the topics generated in the cMOOCs (Xu & Du, 2021).

It was found that knowledge in connectivist learning demonstrates new characteristics in terms of, for example, the connotation, structure, producers, vitality, forms of media, and production and transmission processes (Chen et al., 2019; Wang & Chen, 2020). The connotation of knowledge is enriched, including dynamic and generative knowledge, empirical and practical knowledge, interdisciplinary and fractional knowledge, and selective and individualized knowledge. Knowledge is time- and context-sensitive, only meaningful in certain contexts; existing in networks formed by individuals, organizations, and machines, and generated, developed, and filtered with fragmented and distributed forms. Knowledge producers are more diversified than ever, and learners with different identities, experiences, and backgrounds can all participate in knowledge production. Problem-driven strategies and collective intelligence aggregation have become the main mechanisms for knowledge innovation. Knowledge evaluation is usually based on whether it can meet individual needs, and the requirements for consensus and normalization have been reduced. The media that carry knowledge is diverse, such as videos, pictures, sounds, texts, and computer programs. The Internet has simplified the processes of knowledge generation and transmission, and a large amount of knowledge can be spread and shared via the Internet the moment it is created.

Supported by the course data, the research team further tested certain characteristics of knowledge based on empirical evidence. Under the same topic, the word2vec algorithm was used to extract words from the cMOOCs and journals. The comparison indicated that knowledge generated from cMOOCs was dynamic, holding a practical orientation and coming from multiple perspectives, while traditional knowledge represented by periodical articles was characterized by

having an academic perspective, holding a theoretical orientation, and being systematic in nature (Li et al., 2020).

New Modes of Knowledge Generation in Connectivist Learning

In the view of connectivist learning, knowledge exists in diverse viewpoints, and knowledge generation should be due to collective efforts (Siemens, 2005). Downes defined it as organic growth knowledge production (Downes, 2012, p. 490). Although some researchers compare it to the mining mode and the constructive mode of knowledge generation, they have not uncovered the intrinsic patterns and evolutionary trends of knowledge generation based on practice. The research team attempted to use ecological evolution analysis and content analysis to explore the characteristics of knowledge generation in cMOOC. In the ecological evolution analysis, cMOOC was viewed as an organism of knowledge generation. There were knowledge adoption, knowledge evolution, and knowledge demise treated as variables in the knowledge generation system, and the quantity of knowledge produced was a function of time. Based on the above settings, a quantitative model of knowledge generation (Lu & Chen, 2019) was built and the content analysis was conducted to code topics and roles of knowledge generation in cMOOC.

In this study, knowledge generation in connectivist learning followed a bottom-up pattern of reiteration and collective intelligence aggregation. The quantified model of knowledge production was proposed, and as the cMOOC1.0 progressed, the proportion of self-generated knowledge by learners and the proportion of knowledge demise both increased, while the proportion of external knowledge input decreased. This shows that cMOOC knowledge is generated via internal reiteration. External information and resources are important at the beginning of knowledge production, and the processing, integration, and recreation of such knowledge by cMOOC learners is crucial to knowledge innovation (Lu & Chen, 2019). The content analysis was used to code topics generated during cMOOC2.0. By treating topics as nodes and building links based on whether different topics involved the same participant, the topic generation network was constructed and visualized. It was found that many similar concepts slowly aggregated in the dynamic generation process, reflecting a bottom-up mode of collective wisdom rather than a knowledge classification system decided by experts' experience (Yang et al., 2020).

Meanwhile, content analysis was used during knowledge generation to divide individuals' roles into three types: opinion producers (who usually identify phenomena or use verbal expressions without clear structures), process promoters (who enhance knowledge generation, like raising questions or expressing viewpoints), and miners of the knowledge (who often reflect or integrate viewpoints). The opinion producers do not necessarily promote the process of knowledge evolution; however, the participation and contribution of other roles are important forces to drive knowledge generation. Furthermore, by analysing 100 knowledge-generation discussions (half of them were responded to by facilitators), it was found that appropriate response from facilitators, like giving timely reminders, raising topics, guiding and focusing attention, can enhance the efficiency of knowledge production and make viewpoints more structured and logical. However, over-responding may stifle or even completely stop the knowledge-generation process (Lu & Chen, 2019).

Patterns of Instructional Interactions in Connectivist Learning

Interactions are the core of connectivist learning (Wang et al., 2014). Although Siemens and Downes did not specifically elaborate on it, the viewpoints on knowledge, learning, courses, teachers, students, and learning environment of connectivism all reflect the fundamental role that interactions play. That is, knowledge in connectivist learning comes from interactions between various entities (Downes, 2012, p. 68), and the formation of networks depends on the proceedings of interactions. Course content is generated through interactions, and the construction of individual learning environments is in effect creating a space for interactions. Wang et al. (2014) proposed the framework for interaction and cognitive engagement in connectivist learning contexts (referred to as “CIE model”), which divides instructional interactions in connectivist learning into operation interactions, way-finding interactions, sense-making interactions, and innovation interactions. The CIE model has become an important theory that provides powerful interpretation and guidance to the research on the patterns of instructional interactions in connectivist learning. Based on the CIE model, the research team further explored the interrelationships between the four levels of interactions, as well as the relationship between the interaction level and the network status.

Interrelationships Between Four Levels of Instructional Interactions in Connectivist Learning

According to the CIE model, interaction in connectivist learning is a networked process with recursion rather than being a linear one. Specifically, each level of interaction affects the other levels. Lower levels of interaction are the foundations and supports of the higher ones, while interactions at higher levels extend the need for lower levels (Wang et al., 2014). The research team used content analysis to code the interaction levels and used lag sequential analysis to test and interpret the interplays between different levels.

This study indicates that interactions at higher levels of the CIE model do not necessarily depend on interactions at lower levels, but interactions at higher levels can prompt the occurrence of interactions at lower levels (Huang et al., 2020). The data used included, 1,004 interactive texts generated through the forums and blogs in cMOOC2.0. Each topic or blog, along with the replies and comments to it, was treated as a separate analysis unit. The texts contained in each unit were coded according to time series to reflect their level of interactions. Following the above procedures, 176 interaction series were created, and lag sequential analysis was then employed to explore the time-series transfer modes of different levels (Figure 1).

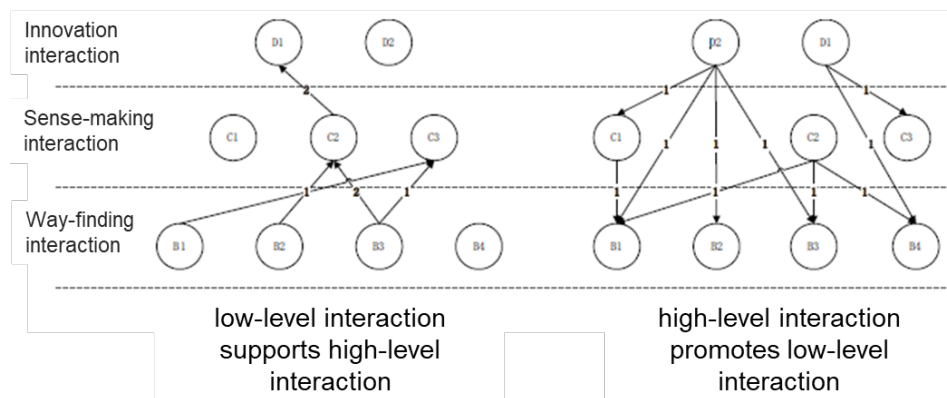
Figure 1 shows that the occurrence of interactions at higher levels does not necessarily depend on interactions at lower levels, although there exists a support relationship in some low-to-high interactions. For example, active direct wayfinding (B2) and helping others by wayfinding (B3) enhance discussions and consultations (C2), further supporting integration for knowledge production (D1). However, some high-level interactions, such as learning products innovation (D2), do not need the support of other lower levels of interaction for their occurrence.

It also can be seen from Figure 1 that higher levels of interactions extend the need for lower levels, characterised by level-jumping, mutual complementation, and weak recursion. Specifically, level-jumping is reflected in the fact that innovation interactions directly extend to wayfinding interactions, and the mutual complementation is reflected in the fact that the paths of two types of innovation interactions interacting with lower interactions are completely different. Besides, the

weak recursion is reflected in the fact that the mediating effect of sense-making interactions is reduced by the path through innovation interactions directly extending to wayfinding interactions.

Figure 1

Path Analysis of Different Levels of Instructional Interactions



Note. From “Instructional interactions in connectivist learning,” by Huang, Chen, Tian, and Wang, 2020, *Distance Education in China*, (09), p.59. (<https://doi.org/10.13541/j.cnki.chinade.2020.09.007>). Copyright 1994-2020 by China Academic Journal Electronic Publishing House.

Relationship Between Level of Interaction and Individual’s Network Status in Connectivist Learning

Based on the connectivist learning viewpoint, learners build connections with people or content through interactions, and thus develop their networks (Wang et al., 2014). The research team used the CIE model to further explore the relationship between individuals’ level of interaction and their status in networks. The level of interactions was coded through content analysis. As well, individuals’ status in the networks was evaluated by social network analysis. A set of indicators, including the in-degree, out-degree, betweenness centrality, eigenvector centrality, closeness centrality, and k-shell, were used to evaluate individuals’ importance in social networks. Further, special roles in the network, such as opinion leader and middleman, were identified by structural holes and the middleman index (Xu, 2020).

The study found that learners who have a higher status and stronger influence in social networks usually have higher levels of interactions. Using the core-periphery matrix and degree centrality to divide participants in the cMOOC1.0 social network into 21 core connectors, 14 peripheral connectors, and 14 marginal learners, it was shown that core connectors had a higher frequency of higher-level interactions, followed by peripheral connectors (H. M. Wang & Chen, 2019). Using 10,598 pieces of interactive data generated by cMOOC1.0, the correlation of the individuals’ network status with their average level of interaction and the highest level of interaction was further examined. The findings indicated that individuals’ network status had a positive correlation with the level of interaction, and that the eigenvector centrality and out-degree can better represent the interaction level. In other words, the more participants that one connected with, and the closer one’s relationship to high-impact participants, the higher one’s level of interaction (Xu, 2020).

In addition, it was also found that special roles with stronger influences in social networks, such as structural hole (identifying the opinion leader in the network) and middleman (identifying the special role of bridging different individuals or groups), usually had a higher level of interactions. Following the filtering rules of “effective size >25 , class degree >0.29 , and constraint <0.25 ,” seven structural holes that had stronger influences in cMOOC1.0 were selected. Meanwhile, the honest broker index was used to select middlemen. The results indicate that the average interaction level and the highest interaction level of structural holes and middlemen, who showed stronger influences, were usually higher than those of others (Xu, 2020).

Two Important Relationships in Connectivist Learning

Connectivism emphasizes the important role that connection plays in learning and mentions that “the pipe is more important than the content within the pipe” (Siemens, 2005, para. 33). It has subverted the traditional opinions on teaching which view the content as the most important element in learning. The research team attempted to explore the relationship between connections and content in connectivist learning. Connectivism emphasizes that facilitators are important nodes in networks and their role is to influence and shape the networks, which subverts the traditional view of teachers as an authority status. This study attempted to reveal the relationship between facilitators and learners based on empirical evidence.

The Relationship Between Connections and Contents in Connectivist Learning

George Siemens (2005) pointed out the importance of the pipe in connectivist learning especially at a time when knowledge is continuously growing, and knowledge is needed but is often not understood. Knowing the sources of valuable information has become a critical skill; in other words, knowing where knowledge is and understanding the methods to obtain it is more important to learners than the knowledge they acquire. Because of this, connectivism emphasizes the importance of building connections. Viewing knowledge innovation as the goal of connectivist learning, social network analysis and descriptive statistics were used to quantify the characteristics of pipes, the keyword extraction algorithms (such as TextRank, and term frequency–inverse document frequency), and descriptive statistics to determine and analyze the contents of the pipes. Correlation analysis was used to compare the importance of pipes and contents in connectivist learning.

Based on the analysis of the cMOOC2.0 data, it was found that pipes and content were equally important to connectivist learning with the goal of knowledge innovation. The structure of knowledge flowing was used to represent pipes, including four characteristics: the breadth, strength, speed, and uniformity, made up of 11 indicators. The content within the pipes was calculated by four characteristics: the breadth, strength, speed, and uniformity of keyword generation, made up of eight indicators. The CIE model was used to code the level of interactions, and correlation analysis and multilinear regression were used to analyze the relationships of pipes or content to interaction levels. The results indicated that the characteristics of pipes had a stronger explanatory power for way-finding interactions and sense-making interactions than that of content ($0.558 > 0.186$ and $0.838 > 0.746$), while they had a weaker explanatory power for innovation interactions than that of contents ($0.155 < 0.303$) (Tian et al., 2020). This means that way-finding interactions and sense-making interactions depend more on the pipes, requiring learners to take the initiative to express

themselves and participate in interactions; innovation interactions, however, are more dependent on the content, which requires learners to have a good grasp of the knowledge itself. Thus, in connectivist learning with the goal of knowledge innovation, the contents within the pipes are as important as the pipes.

The Relationship Between Facilitators and Learners in Connectivist Learning

In connectivist learning, teachers are defined as course facilitators, and shapers and influencers of networks (Wang et al., 2014). They are demonstrators and learners' companions in the journey of learning, but not decision-makers or guides (Dron, 2013). Based on experiences in planning and implementing cMOOCs, Siemens (2010) viewed facilitators as important nodes in networks and defined seven roles for them: magnifying important information or topics in the network, planning and arranging key learning nodes, helping learners do way-finding and sense-making in complex information environments, aggregating fragmented contents, filtering confusing and disturbing information, demonstrating, and staying in the network. By analysing data from the cMOOCs, the research team further tested the facilitators' roles and functions in networked learning.

First, at the beginning of the connectivist learning, facilitators had a significant effect on most learners. As the learning progressed, however, more core learners emerged, and the status of facilitators gradually weakened. The research team used the roles of participants (e.g., academics, business members, administrators, teachers, students, facilitators) as nodes to construct cMOOC1.0 networks and found that facilitators received more attention and replies indicated by relatively higher in-degree (Guo et al., 2020). Further, in the time dimension, at the beginning of learning, there were no apparent groups in the networks, and facilitators were in a position of strong influence, meaning that traditional learners still maintained a viewpoint that teachers were naturally the authorities. As they increasingly got used to connectivist learning, the participants self-organised into various groups. As well, although the facilitators occupied the core position in large groups in the early period, core learners continuously emerged and became the core of their group, even their network status exceeded the facilitators, meaning that the power of facilitators gradually diminished (Xu, 2020).

Second, facilitators' functions in the networks were to promote the building of connections and to influence and shape networks. In cMOOC2.0, it was found that after a live event (organized by the facilitators) was completed, the structure of the social network was more compact, reflected by the highest average degree and density, indicating that the activity that the facilitators participated in increased learners' willingness to interact with each other (Yang et al., 2020). Comparing the parameters of the social networks before and after the facilitators' nodes were deleted, it was shown that after the deletion, the density, complexity, and regularity of the social networks decreased, while the randomness and modularity increased. This means that in the absence of facilitators, learners had their self-organised communities; however, after facilitators joined them, the learners organised themselves following a set of rules, and their connections were closer. In other words, facilitators played the roles of controlling, regulating, maintaining, and enhancing connections, and influenced and shaped the development of networks (Yu et al., 2020).

Discussion and Conclusion

This paper reviews the findings of research conducted over 3 years based on the first cMOOC in China from four aspects, including a) complex network characteristics, b) patterns of knowledge generation, c) patterns of instructional interactions, and d) two important relationships between pipe and content and between facilitators and learners. This research contributes to the development of connectivism in three ways. First, existing viewpoints of connectivism were tested and substantiated based on empirical evidence, such as the roles and functions of facilitators in influencing and shaping network development. Second, the principles of connectivist learning were further developed. For instance, connectivism highlights that learning is the process of building networks. And we further revealed the static and dynamic characteristics of complex networks in connectivist learning. Siemens (2006) proposed the concept of soft knowledge and Downes (2012) raised the concept of the growing mode of knowledge production; this research further examined the connotations and characteristics of networked knowledge and identified three characteristics of knowledge production modes (internal reiteration, group intelligence aggregation, and the bottom-up approach), and interpreted the three roles and functions of knowledge producers. The CIE model proposed four levels of interaction (Wang et al., 2014); this research further explored the time-series relationships between lower-level interactions and higher-level interactions. Third, some viewpoints of existing research on connectivism were improved here. Connectivism emphasizes that “the pipe is more important than the content within the pipe” (Siemens, 2005, para. 33); this research found that, for connectivist learning with the goal of knowledge innovation, the contents within the pipes are as important as the pipes.

Findings from our research also have practical implications for promoting online learning in the new era. As we all know, the COVID-19 outbreak made online learning an important way for students to learn. However, the main format of online learning has been to merely move traditional classroom learning onto the Internet. Although it has been 16 years since connectivist theory was first proposed, there are very few online courses that reflect the characteristics of the new learning theory. In China, the cMOOC developed by this research team is the only connectivist-based online course. The main reason for this gap is insufficient research on the patterns and practical methods of connectivist learning. Although certain results were achieved in recent years, there are still many questions to be answered, such as the evolutionary patterns and factors of the three networks, the interplay mechanism between different networks, the modes of instructional design guided by connectivism, the impact of connectivist learning on learners’ capacity development, further exploration of the characteristics of knowledge and its evolutionary patterns, the relationship between individual learning and collective learning, and the factors that influence the level of interaction. This study suggests that the above questions be treated as frontline tasks in the fields of online learning, and that by sharing the research findings in China on connectivist theory, researchers and practitioners could be encouraged to conduct more systematic and in-depth research in order to refine connectivist theory and develop e-learning courses more effectively and efficiently.

Acknowledgements

This research is supported by the project “Research on the management of education reform and innovation in the era of ‘Internet plus’” funded by The National Natural Science Foundation of China (NSFC) [Grant No. 71834002].

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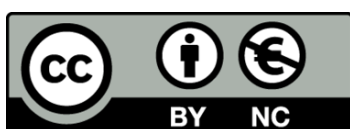
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