Canadian Journal of Learning and Technology
Revue canadienne de l'apprentissage et de la technologie

CJLT RCAT
Canadian Journal of Learning and Technology
La Revue canadienne de l'apprentissage et de la technologie

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Analyze dynamique de l'évolution du réseau social dans le cMOOC basé sur le mode RSiena

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Cite this article

Article abstract

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Abstract

The network is a key concept which has been highly valued in connectivism. Research about the static characteristics of social networks in connectivist learning has been carried out in recent years, however, little knowledge exists regarding the principles of network evolution from a dynamic perspective. This article chose the first connectivist massive open and online course (cMOOC) in China, "Internet plus Education: Dialogue between Theory and Practice" as the research object, using the dynamic analysis method of social networks which is based on stochastic actor-oriented models, to reveal the influence of the individual attributes and network structural attributes on the dynamic evolution of social networks in a cMOOC. We found that: 1) the learners with the same sex, the same social identity, and the same type of behaviour tendency found it much easier to interact with each other; 2) there is a heterogeneous phenomenon with course identity, meaning that compared to communicating with other learners, learners are more inclined to reply to a facilitator; and 3) the reciprocity and transitivity have significant effects on social network evolution. This study is valuable for understanding the network evolution and has implications for the improvement of cMOOC design, in turn improving the online learning experience for cMOOC learners.

Keywords: cMOOC; Social network; SIENA; Evolution; Interaction; Connectivism

Résumé

Le réseau est un concept essentiel qui a été fortement valorisé dans le connectivisme. Quelques recherches ont été menées ces dernières années sur les caractéristiques statiques des réseaux sociaux dans l'apprentissage connectiviste. Cependant, il existe peu de connaissances sur les principes

d'évolution des réseaux d'un point de vue dynamique. Cet article a choisi le premier cours connectiviste de formation en ligne ouverte à tous (cMOOC) en Chine, "Internet plus Éducation : Dialogue entre la théorie et la pratique" comme objet de recherche, en utilisant la méthode d'analyse dynamique des réseaux sociaux qui est basée sur des modèles stochastiques orientés vers les acteurs, pour révéler l'influence des attributs individuels et celles des attributs structurels du réseau sur l'évolution dynamique des réseaux sociaux dans un cMOOC. Nous avons constaté que : (1) les apprenants ayant le même sexe, la même identité sociale et le même type de tendance comportementale trouvent qu'il est beaucoup plus facile d'interagir les uns avec les autres ; (2) il existe un phénomène hétérogène avec l'identité du cours, ce qui signifie que par rapport à la communication avec d'autres apprenants, les apprenants sont plus susceptibles de répondre à un facilitateur ; (3) la réciprocité et la transitivité ont des effets significatifs sur l'évolution des réseaux sociaux. Cette étude est utile pour comprendre l'évolution du réseau et a des implications pour l'amélioration de la conception du cMOOC, améliorant à son tour l'expérience d'apprentissage en ligne pour les apprenants du cMOOC.

Mots clés : cMOOC ; réseau social ; Siena ; évolution ; interaction ; connectivisme

Introduction

Connectivist learning reveals a new idea to solve complex problems and create knowledge by continuously connecting high-quality nodes, especially adapting to the new characteristics of the networked knowledge in the era of "Internet +" (Downes, 2012). When the needs and problems are constantly changing, and the knowledge becomes dynamic, uncertain, and unpredictable, it's more important to build good networks that can adapt to change than to memorize and store knowledge (Downes, 2017). The cMOOC is a typical practice of connectivism. Different from traditional online courses represented by the eXtended massive open online courses (xMOOC), there are new learning rules existing in connectivist learning. Understanding the new rules is crucial to the design of cMOOCs and improving the learner's learning experience. According to connectivism, learning is a process of connection building and network development (Siemens, 2005). The characteristics and interaction mechanism of the three networks - internal cognitive neural network, concept network, and social network - are the key issue in revealing learning rules (Wang & Chen, 2017). Complex social networks are generated by participants through continuous interaction in distributed learning space, and the network structure expands and evolves with the deepening of interaction. The exploration of the dynamic evolutionary mechanism of networks can provide fundamental support for analyzing the interactive tendency of connectivist learners and assist facilitators to improve design and service. In October 2018, Professor Chen Li and her team from Beijing Normal University designed the first cMOOC in China, "Internet plus Education: Dialogue between Theory and Practice". By August 2021, the cMOOC had been delivered six times and the learning data

received from these six offerings were used for this study which revealed the dynamic evolution principles of social networks. Using data from the platform of cMOOC2.0, and with the help of the stochastic actor-oriented model, this study aimed to measure and explain how the social network in cMOOC forms and evolves.

Literature Review

Social network analysis (SNA) is used to quantify the structure of social networks at various levels (role, two-dimensional, three-dimensional, etc.), and to better explain the basic problems in connectivist learning from the perspective of the network. How are connections formed and maintained? How do roles and relationships affect learning?

Benefiting from the development of big data and complex network analysis methods, SNA has been applied to MOOC studies and much research has been carried out to explore interaction patterns in forums, blogs, and microblogs. Among them, Chinese researchers mostly focus on summarizing the characteristics and analyzing the static properties of social networks. For example, reciprocity was used to measure the number of bilateral relationships and judge one-way interaction with the help of average distance and network diameter (Song et al., 2014). Block model analysis was carried out to reveal the internal sub-structure of the network, reflecting the closeness and breadth of interaction among members (Guo et al., 2020). Additionally, interaction tendency among bloggers (Wang et al., 2012) and the ecological structure of the online community; the relationship between subgroups was visualized and analyzed to find special roles like broker, sender, and receiver (Liu et al., 2018). Lastly, some studies used in-degree, out-degree, betweenness centrality, and other indexes to build an assessment model of individual network status and identify the differences in academic performance of individuals with different importance (Xu & Du, 2021; Liang, 2018). Very few researchers have analyzed network evolution from a dynamic perspective, such as counting density, edges, and nodes in different periods to reflect the evolution of social networks (Wu et al., 2016). In the West, this research direction has received growing attention over recent years. Yang et al. (2013) measured the different periods of the network to explore how the learners interact with the existing community; Kellogg et al. (2014) studied peer-assisted learning in MOOC forums by SNA and found that MOOCs can more effectively foster the networks and promote the occurrence of peer-assisted learning. These types of studies revealed the evolution phenomenon of the social network by generating static snapshots of a network at different points but did not connect the observed behaviours to the underlying effects of network structure and the characteristics of learners (Zhang et al., 2016).

Research on connectivist learning in China and abroad has grown since 2010. More current research is attending to learning environments and resources, theory analysis, interaction patterns,

characteristics of learners, and activity design. In recent years, the static characteristics and relationships of networks have received growing research attention, such as the structure of the whole social network (Wang et al., 2018), the correlation between individual network status as well as other variables like academic performance and concept generation (Duan et al., 2019; Xu & Chen, 2019). Despite the extensive literature examining SNA, one issue that remains less explored is the dynamic evolution mechanism of the network, which may lead to the interpretation of how connectivist learning happened. Therefore, it is prudent to use the simulation investigation for empirical network analysis (SIENA) to explore the characteristics of structural changes of networks in cMOOC to better understand the social complexity of connectivist learning. The laws behind its evolution can help us understand how interaction occurs in connectionism learning and provide references for optimizing learning support services and recommendation mechanisms in cMOOC, to improve the way-finding efficiency and learning experience of cMOOC learners.

Hypothesis

The establishment and deletion of connections in a network is the fundamental cause of network topology change. Earlier studies evaluated found that the individual attributes and network structure attributes had an influence on the evolution of relationships in social networks (Albert & Barabasi, 2001). This study also discusses the effects of these two dimensions on the evolution of social networks in cMOOCs.

Effects of Individual Attributes (Homophily)

The homophile was first proposed by Lazarsfeld and Merton in 1954, which suggests people are more inclined to establish relationships with individuals who are like themselves or have the same attributes (McPherson et al., 2001). It is reasonable to assume that homophile is important to the development of learners' interaction. The spread of knowledge and exchange of ideas is much more likely to occur between similar groups than among other groups (Rogers, 1995, p. 18). In previous relationship analysis of online communities, demographic attributes (like sex and age) and experience similarity (like illness, etc.) were often used as factors to determine homophiles (Wu et al., 2017). This study selected five individual attribute factors: 1) sex ("male" or "female"); 2) field of interest ("curriculum and resource design," "technology and product development," "law and method research," "service and marketing," or "policy and institutional innovation"); 3) social identity ("education manager," "industry elite," "teacher," or "student"); 4) course identity ("facilitator" or "learner"); and 5) behavioural tendency ("like," "blogging," "follow," or "comment").

The reasons for selecting the above attributes are as follows: 1) sex is treated as a significant factor influencing the establishment of relations in online communities; 2) field of interest and

social identity can reflect the similarity of participants' experiences; 3) course identity can help us understand and verify the role of facilitators in the construction of connectivist social network; and 4) behavioural tendency is used to distinguish the influence of individual interactive habits on connection establishment. Therefore, the following hypotheses are proposed in this study:

- **H1a**: With the development of connectivist learning, participants of the same sex are more likely to interact with each other.

- **H1b**: With the development of connectivist learning, participants in the same field of interest are more likely to interact with each other.

- **H1c**: With the development of connectivist learning, individuals with the same social identity are more likely to interact with each other.

- **H1d**: With the development of connectivist learning, the frequency of learners' interaction with other learners is much higher than that with facilitators.

- **H1e**: With the development of connectivist learning, individuals with the same behavioural tendency are more likely to interact with each other.

Effects of Network Structure Attributes

Reciprocity

Reciprocity is an important evaluation index of the interaction in networks, which is a two-dimensional statistical process calculated by a union vector. Reciprocity refers to the back-and-forth in communication (if A replies to B, then B replies to A). Former studies have shown that in the process of interaction, learners not only express their own views but also establish communication relationships with others by replying to the content posted by others. Reciprocal interaction is conducive to promoting cognitive socialization (Arvaja et al., 2003). Therefore, the following additional hypothesis is proposed in this study:

- **H2**: In connectivist learning, there is an increasing tendency towards reciprocity in social networks over time.

Transitivity

Transitivity, that is, if A is related to B, and B is related to C, then A is related to C, makes sense for networked learning. In the virtual environment, it is the transmission of trust and opportunity in the learners' community. cMOOC learners can access other learners' personal home pages by course platform to find out its focus on the list. In other words, due to the mediation of B, there is more opportunity for A and C to connect with each other. Kossinets and Watts (2006) conducted an experimental study and found that the more common friends two individuals have, the likelihood of establishing a relationship will increase significantly. At the same time, different learning groups

can provide learners with different resources, and learners can obtain the resources they need by communicating with different peers. In other words, the more obvious the transitivity in the network is, the greater the supporting effect for learning will be. Moreover, transitivity can also increase network closure. In a closed group, trust can be established among members to form a mutually supportive environment. Therefore, the following hypothesis is proposed in this study:

- **H3**: In connectivist learning, there is an increasing tendency towards transitivity in social networks over time.

Preferential Attachment (Matthew Effect)

The Matthew effect represents a positive feedback loop generating a power-law distribution in a network (Zhang et al., 2016). In other words, the rich get richer. In education, it can be understood that individuals in the center of the network or with greater influence will receive more attention and interaction, which reflects the polarization phenomenon in the network. Once these important individuals quit, it will cause great damage to the whole social network, and even lead to the collapse of the network structure and affect the continuation of the whole interaction in learning. On one hand, there will be central participants in a highly centralized network and it's conducive to the efficient transmission of information. On the other hand, the high imbalance of power in such networks isn't beneficial to collective intelligence communication, and the network structure is fragile. Zhang et al. (2016) discovered that there is a tendency towards preferential attachment in MOOC networks. Therefore, the following hypotheses are proposed in this study:

- **H4**: In connectivist learning, there is a tendency of Matthew effect in social networks over time.

Methods

Context and Data Collection

The cMOOC2.0 offering of "Internet plus Education: Dialogue between Theory and Practice", was selected as the research context in this study. There were 1,550 Chinese learners registered and it ran for 12 weeks. The course was built on five themes: 1) the philosophy of "Internet plus education"; 2) the fusion of online and offline learning spaces; 3) co-construction and sharing of social education resources; 4) consumption-driven education supply-side reform; and 5) accurate and efficient education management model. During the course, learners can establish social network relationships through various behaviours including liking, commenting, and discussing. The data collected in this study includes personal attribute data (sex, the field of interest, social identity, learning identity), individual behaviour frequency data (like, blogging, follow, comment), and network construction data (interactive data). In the end, 22,468 pieces of behavioural data were

collected including 7,473 pieces of "like" data, 4,083 pieces of "follow" data, 9,654 pieces of "comment" data (including posting and reply), and 1,258 pieces of "blogging" data.

In this study, the social network of cMOOC2.0 was divided according to the running time of each theme. The basic attributes of the network in the eight stages are shown in Table 1. The Jaccard coefficients of the two adjacent stages were calculated, which were 0.341, 0.833, 0.869, 0.975, 0.935, 0.934 and 0.963 (all greater than 0.3), indicating that the network was stable and smooth between the two continuous periods. Therefore, the eight periods were properly divided and suitable for SIENA analysis.

Table 1

Basic Attributes of Social Networks in Eight Stages

	Guiding Week	Theme 1	Theme 2	Theme 3	Mid-term	Theme 4	Theme 5	Ending Week
Run Time	03.08 -03.19	03.20 -04.02	04.03 -04.16	04.17 -04.30	05.01 -05.07	05.08-05.21	05.22 -06.04	06.05 -06.15
Nodes	688	1154	809	804	251	680	734	477
Edges	2105	5984	2682	2990	496	2316	3216	1421
Density	0.006	0.017	0.020	0.023	0.024	0.025	0.027	0.028
Average Degree	3.000	8.787	10.554	12.148	12.465	13.326	14.266	14.816

Methods

Based on the stochastic actor-oriented model, this study chooses the R package "RSiena" as the tool for dynamic analysis of social networks in cMOOC. The advantage of this model is that it can analyze the dynamic evolution of the network based on the Markov chain. According to the stochastic actor-oriented model, the formation and evolution of the network are determined by the actions of nodes in the network, and each node decides to establish, maintain, or cancel connections by themselves, which ultimately affects the change of the entire network. The model takes the change of the network as the dependent variable, and the node attributes, network structure, and other random variables as the factors that change the connection of the node (Snijders et al., 2010).

The objective function is used to calculate the overall structural effect preferred by nodes among all possible network structures. Objective function mainly depends on structural effect and

covariate effect. The structural effect measured in this study includes "reciprocity", "transitive triplets", and "out-degree related popularity (SQRT)". Reciprocity calculates the probability of B's reply to A in the case of A having replied to B. Transitive triplets are represented by the number of connections between individuals and their friends' friends, which can reflect the tendency of transitivity in the networks. The SQRT is used to measure the attractiveness of an actor, that is, an individual who has received many responses is likely to be responded to by others. The covariate effect is based on the internal factors to measure the dynamic characteristics of the network, and this study chose the "same V" effect to measure the tendency of the node's connection to others with equal attribute values. This study focused on five attributes (sex, areas of interest, social identity, course identity, and behavioural tendency) to reflect the effects of homogeneity on the evolution of social networks. If the estimated value of the same V effect of an attribute is positive, then two nodes with the same value of this attribute are more likely to form a connecting edge. In the SIENA model, the conditional method of moments estimation was used for data analysis, and the total number of changes in the observed network was used to represent the conditional variables. If the aggregation of the model is too low (i.e., the value of t-ratios in the model is higher than 0.25), the obtained results will be taken as the starting value and analyzed again until the aggregation degree reaches the standard (Ripley et al., 2015).

Results

Effects of Individual Attributes on Evolution of Social Networks in a cMOOC

This study proposed hypotheses on the influence of sex, field of interest, social identity, course identity, and behavioural tendency on the evolution of the social network in a cMOOC. Table 2 shows the estimated results of the stochastic actor-oriented model. In terms of the t-ratios value of each attribute, the model fitting precision of "(1) → (2)" (from guiding week to theme 1) and "(5) → (6)" (from mid-term week to theme 4) was poor (t-ratios> 0.1). The main reason is that there are no specific themes and learning tasks during the guiding week and the mid-term summary week. Consequently, the results cannot reflect the actual learning situation of cMOOC and cannot interpret the evolution law of social networks in cMOOC. T-ratios in other periods were mostly less than 0.1, so the significance of effect values in other periods should be mainly considered in the analysis. The method to judge whether the effect is significant or not is to divide the value outside parentheses by the value inside parentheses. If it is greater than 2, the effect is proved to be significant at the level of 0.05.

Table 2

Results of Covariate Effect by Rsiena

	(1)→(2)	(2)→(3)	(3)→(4)	(4)→(5)	(5)→(6)	(6)→(7)	(7)→(8)
Sex	-0.0629	0.4071**	0.3339**	0.6630	0.1510	0.1507**	0.0055
	(0.0348)	(0.0688)	(0.0474)	(0.5085)	(0.2121)	(0.0741)	(0.0626)
t-ratios	**-0.1851**	0.0434	-0.0370	-0.0890	**-0.3613**	-0.0556	**-0.1581**
Field of interest	-0.1890**	-0.0075	0.4021**	0.0308	0.0267	0.0042	-0.2132**
	(0.0483)	(0.0539)	(0.0486)	(0.1829)	(0.3190)	(0.0597)	(0.1050)
t-ratios	**-0.3993**	-0.0325	**-0.2427**	-0.0864	**-0.4309**	**-0.2494**	-0.0062
Social identity	0.0621	0.4497**	0.5640**	0.2563	1.0923**	0.3905**	0.2898**
	(0.0331)	(0.0592)	(0.0441)	(0.1364)	(0.1184)	(0.0791)	(0.0960)
t-ratios	0.0798	0.0065	0.0003	0.0507	**0.1840**	0.0705	0.0105
Course identity	-0.5952**	-0.5760**	-0.1464	-0.9789**	-0.8097	-0.6957**	-0.8660**
	(0.1472)	(0.0529)	(0.0750)	(0.2665)	(0.5233)	(0.1119)	(0.1484)
t-ratios	**0.5839**	0.0389	**-0.2724**	**-0.2363**	**-0.5483**	**-0.1442**	0.0425
Behavioural tendency	0.1286**	0.0665	0.5176**	0.4353	0.4032**	0.3104**	0.2646**
	(0.0370)	(0.0388)	(0.0756)	(0.4836)	(0.1227)	(0.0654)	(0.1068)
t-ratios	**-0.1648**	-0.0139	0.0573	-0.0690	**-0.2977**	0.0006	**-0.1505**

** significant at $p<0.05$; the values of t-ratios in bold mean the model fitting precision of it was poor.

Impact of "sex" on the Evolution of Social Networks in cMOOC

As shown in Table 2, the absolute value of t-ratios of sex was less than 0.1 during the main theme-learning period. In the evolution stages of "(2) → (3)", "(3) → (4)" and "(6) → (7)", sex had a significant effect on network changes and the estimated value of parameters was positive, up to 0.6630, indicating that it is easier for learners of the same sex to establish connections, which **confirms hypothesis H1a**. Earlier studies have shown that people of the same sex have higher

similarities in thinking mode, perspective, and mentality, and are more likely to understand each other and establish a sense of trust in the process of communication on the same topic (Durant et al, 2012; Wu et al., 2017). cMOOC learning obviously follows this rule as well.

Impact of "Field of Interest" on the Evolution of Social Networks in cMOOC

According to the estimation results of the t-ratios, only the three evolution stages of "(2) → (3)", "(4) → (5)", and "(7) → (8)" have a good model fitting performance. Unfortunately, the field of interest only has a significant influence on the network evolution of "(7) → (8)" and the parameter estimation value is negative, meaning learners with different fields of interest are more likely to establish connections. It's obvious that the influence of fields of interest on network changes is unstable and insignificant in most cases, i.e., **H1b is rejected**. cMOOC learners will contact vast amounts of generative content which is not in accordance with the areas of interest, and most content is interdisciplinary which supports discussion from multiple perspectives. Thus, learners' interaction mainly depends on whether the idea can resonate or provoke thought, namely the learner may publish or reply to content in different areas.

Impact of "Social Identity" on the Evolution of Social Networks in cMOOC

As shown in Table 2, except for "(5) → (6)", the absolute value of t-ratios of social identity was less than 0.1, therefore, the model results are reliable. Social identity has a significant effect on the evolution of adjacent networks, and the parameter estimation value was positive, indicating that participants with the same social identity were more likely to establish connections. **H1c is accepted**. Individuals with similar social identities tend to have similar discourse systems, similar experiences, similar knowledge backgrounds and abilities, so there are more common topics that they are familiar with; and the problems they faced and the perspective they followed are also similar, so they are more likely to connect with each other. Therefore, learners with the same social identity are more likely to interact with each other.

Impact of "Course Identity" on the Evolution of Social Networks in cMOOC

According to the estimation results of t-ratios, only "(2) → (3)" and "(7) → (8)" models have better fitting effects, where the influence of course identity is significant at the level of 0.05, and the estimated value of parameters is negative, indicating that individuals with different course identities are likely to establish connections. That is, it is easier to establish a connection between facilitators and learners in cMOOC, so **H1d is rejected**. Connectivism emphasizes the interaction between learners, and that learners promote the generation of content, and the aggregation and contribution of learners' experience is the main way to solve problems (Chen et al., 2019). This result shows that in this cMOOC, facilitators are the important roles for most learners, and most learners are still willing to actively establish and maintain contact with facilitators. However, this result still needs to be verified in other cMOOCs.

Impact of "Behavioural Orientation" on the Evolution of Social Networks in cMOOC

As shown in Table 2, the t-ratios were less than 0.1 in "(3) → (4)" and "(6) → (7)" phases, and behavioural tendency had a significant effect on network changes with positive estimated parameter values. It means that learners with the same behavioural tendency were more likely to establish connections, so **H1e is accepted in some cases**. There are a variety of interactive ways provided in cMOOC, including posts, thumbs up, comments, concerns, etc. In general, the learner's behaviour reflects their habitual and preferred modes of interaction. Meanwhile, learners will pay particular attention to their preferred interactions. In other words, learners with the same interaction behaviour may have more opportunities to connect because they communicate based on their behaviour type.

Effects of Network Structure Attributes on Evolution of Social Networks in a cMOOC

This study focuses on the effects of reciprocity, transitivity, and preferential attachment on the evolution of social networks in cMOOC. Table 3 shows the estimated results by the RSiena model.

Table 3

Results of Network Structure Attributes' Effects by RSiena

	(1)→(2)	(2)→(3)	(3)→(4)	(4)→(5)	(5)→(6)	(6)→(7)	(7)→(8)
Reciprocity	2.2091**	1.5421**	1.9210**	3.5725**	4.9948**	1.7076**	1.4944**
	(0.0815)	(0.1602)	(0.1053)	(0.4516)	(0.6085)	(0.1532)	(0.2887)
t-ratios	0.0358	0.0445	**0.1248**	0.0021	-0.0845	0.0697	-0.0596
Transitivity	0.1049**	0.0739**	0.1072**	0.1100	0.5165**	0.1376**	0.1172**
	(0.0068)	(0.0030)	(0.0055)	(0.0901)	(0.0556)	(0.0083)	(0.0112)
t-ratios	0.0347	0.0414	0.0915	**-0.2297**	-0.0524	0.0679	-0.0907
Preferential attachment	0.1608	0.7270**	0.2665	0.6813	-1.3415	-0.0647	0.1158
	(0.1440)	(0.1069)	(0.1944)	(2.7710)	(1.2880)	(0.1553)	(0.1664)
t-ratios	0.0989	-0.0760	**-0.1455**	**-0.2263**	**-0.1297**	**-0.1494**	**-0.1226**

** significant at p<0.05; The values of t-ratios in bold mean the model fitting precision of it was poor.

Impact of "Reciprocity" on the Evolution of Social Networks in cMOOC

As shown in Table 3, the absolute value of t-ratios in other periods except "(3) → (4)" was less

than 0.1. Reciprocity has a significant effect on network changes at the level of 0.05 and the estimated parameter values are positive, which range from 1.4944 to 4.9948 in different periods. It indicates that the reciprocity of social networks in cMOOC increases over time. **H2 is accepted**. During cMOOC learning, there are vast amounts of generative, fragmented, and distributed contents in an open network environment, and the learners need to independently filter unprofitable information and build valuable connections. It should be noted that the comments or replies from others can be presented to learners by the system automatically, which shortens the way-finding path between senders and receivers. Therefore, compared to others, it's easier to establish a two-way interaction.

Impact of "Transitivity" on the Evolution of Social Networks in a cMOOC

As shown in Table 3, for single t-ratios, very few absolute values are greater than 0.1, indicating good model fitting performance. The effect of transitivity on network changes is significant at the level of 0.05. The estimated values of parameters are positive, meaning that individuals in cMOOCs were more inclined to establish contacts with friends' friends. As the social network changes over time, the transitivity (network closure) continues to increase and the network cohesion is enhanced, which **confirms hypothesis H3**. This is because in community activities, individuals usually have a higher sense of trust towards friends' friends, and the behaviours or interactions of the learners they focus on are more likely to lead to their attention. Through the intermediary role of friends, the opportunity to communicate with their friends also greatly increased, thus promoting the interactions between individuals and their friends' friends.

Impact of "Preferential Attachment" on the Evolution of Social Networks in cMOOC

According to the model fitting results, the fitting effect of the network evolution model was not good from theme 2 forward because only the absolute value of t-ratios in "(2) → (3)" was less than 0.1. The effect of preferential attachment in this period is significant at the level of 0.05, and the estimated value of parameters is positive, indicating that there is a Matthew effect in the social network at the early stage of cMOOC learning, that is, individuals at the centre of the network with greater influence will gain more attention and interaction in later learning. This is because when new learners enter the learning community, active learners are more likely to attract their attention in the unfamiliar learning environment. But with the development of learning, learners gradually adapted to the complex information environment, the problem-driven and theme-based discussion will become the main tendency of interaction. From the whole stage of the course, the tendency of a preferential attachment effect is not stable, and the Matthew effect is not obvious in the evolution of social networks (although the model fitting effect is not good, the parameter estimates are sometimes positive and sometimes negative), so the hypothesis **H4 is rejected**. This effect still needs to be verified in more cMOOC contexts.

Discussion and Conclusions

Supported by the first cMOOC in China, using the stochastic actor-oriented model, this study analyzes the factors influencing the dynamic evolution of social networks from two dimensions of individual attributes and network structural attributes and reveals the evolutional mechanism of social network structure in a cMOOC. The results will provide support for designing more effective activities, recommendations, and pathfinding mechanisms.

This study found that there is homogeneity during the evolution of social networks in cMOOC. Connectivist learners are more inclined to communicate and establish connections with other learners of the same sex, social identity, and behavioural tendency. This finding has also been confirmed in former studies on the evolution of online community relations in other fields. Social relationships are easier to establish and maintain between individuals with similar identical attributes (Wang et al., 2008; Durant et al., 2012). Therefore, to promote the formation of a closer social network structure and the establishment of connections between learners, the partner recommendation mechanism can be designed according to the similarity of sex, social identity, and behavioural tendency, so that the promoting effect of curriculum design on wayfinding can be brought into play.

However, there is a heterogeneous phenomenon during the evolution of social networks in cMOOC in terms of course identity. Compared to communicating with other learners, learners are more inclined to reply to the content posted by the facilitator. Kellogg et al. (2014) found that students play an important role in promoting forum interaction. The connectivism theory also emphasizes that learners are the main contributors and creators of course content, and connectivist learning relies on learners' active participation (Anderson, 2009). This study takes the cMOOC as the research context, due to the influence of traditional education styles, the idea of teacher-centred, and the teacher as the authority still affects most Chinese learners. For most connectivist beginners, teachers are important nodes in the network and the information amplified and spread by teachers is more valuable and influential (Zhang et al., 2016; Xu, 2020). In this type of network, the information transmission speed of the facilitators to learners is much faster than that between learners, however, the number of learners in cMOOCs tends to be one hundred times as many as the number of facilitators. Therefore, this heterogeneous phenomenon is not conducive to the rapid dissemination of information in the network. When designing cMOOCs, facilitators, as an important learning partner, need to help beginners make diversely wayfinding through demonstration (Dron, 2013) and connectivism emphasized learning support distributed in the community (Downes, 2017) can establish incentive mechanism to promote peer support and role models, which is key to dealing with this challenge in mass group learning.

In terms of network structural attributes, we also find that reciprocity and transitivity have significant effects on the evolution of social networks in cMOOCs. This finding is reasonable and consistent with previous research. For example, Zhang et al. (2016) found that MOOC learners tend to reply to reciprocal partners and establish connections with others in a transmission way. Waite et al. (2013) proved the reciprocal relationship of learners' participation in MOOCs by qualitative research. This study demonstrated that there are some significant effects of reciprocity and transitivity on social networks in cMOOCs as same as xMOOCs. Therefore, when designing cMOOCs, the reciprocity and transitivity can be used to optimize the functional modules of the platform, whereby the original content list arranged in chronological order can be changed (Buder et al., 2015) to highlight high-quality and learner-related content to guide the attention distribution of learners. As an alternative, the reciprocity and transitivity can be used to optimize the partner and content recommendation mechanism, such as pushing the posts or comments from friends and guiding learners to actively comment on the content posted by individuals with high response rates.

In conclusion, this study is a beneficial attempt to reveal the dynamic evolution laws of social networks in connectivist learning based on empirical evidence, which to some extent supports the improvement and optimization of cMOOC design in learning support services, environment, recommendation mechanism, and other aspects. However, the model fitting performance of two attributes (course identity and preferential attachment) is not sufficient in this study, and this study is rooted in a Chinese educational practice context; that is, the results and discussions still need to be verified in more cMOOC contexts with various cultural backgrounds. Meanwhile, further studies should also be explored to reveal the impact of intervention strategies on the evolution of social networks.

Acknowledgements

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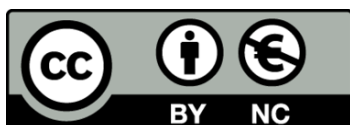
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