An Analysis of the Categories and Structures of Expertise for Students' Cognitive States

https://doi.org/10.3991/ijet.v18i01.37123

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Abstract—Knowledge networks play an important role in the process of knowledge acquisition and sharing by students. An analysis of their complex structural features is required for the connectivity between students and knowledge. Existing research lacks insight into the internal structural features of knowledge networks constructed from expertise. There is also a lack of effective methods for constructing personalised knowledge networks for students' cognitive states. This paper analyses the categories and structures of expertise for students' cognitive states, and presents in detail a grey prediction algorithm to identify students' cognitive states. Then, the paper presents a typological description of the knowledge nodes in the expertise network for students' cognitive states, and analyses the knowledge network structure from the perspectives of paths and statistical properties. After that, the paper gives a method for analysing the knowledge flow of the expertise network. The experimental results validate the effectiveness of the proposed method.

Keywords—cognitive states, categories of expertise, knowledge network structure analysis

1 Introduction

With the development and popularity of the Internet, online learning methods that meet personalised learning needs for students are increasingly accepted and recognised [1–8]. However, there are differences in the needs of students with different cognitive levels for learning resources [9–12]. To prevent students from becoming "knowledge lost" when faced with a huge load of learning resources, it is necessary to predict students' cognitive levels and correlate them with the appropriate expertise for their learning [13–15]. Knowledge networks play an important role in how students acquire and share knowledge. Connecting students to knowledge requires an analysis of its complex structural features [16–21].

In terms of student cognitive level assessment, Hou [22] introduced the concept of Teaching for Ability (TFA) based on traditional Internet teaching, using big data to calculate students' cognitive abilities and using the assessment results of students' cognitive abilities to drive a tailored Internet learning programme for each student on a case-by-case basis. Educational programmes for students with low cognitive ability were identified in the data analysis. In terms of knowledge association, Xu and Jiang [23] proposed a personalised recommendation algorithm for online educational resources based on knowledge association. Firstly, online educational resources were collected based on association rules. Secondly, the firefly algorithm was used to classify the online educational resources. Then, a vector space function was constructed to filter the classified online education resources. Online learning platforms are prone to information overload, as they contain a large number of diverse resources. To address this problem, Jia et al. [24] explored collaborative filtering recommendation (CFR) for online learning resources based on a knowledge association model. Knowledge units were extracted from the semantic information of online learning resources (OLRs) to build a knowledge association model for OLR recommendations. A CFR algorithm was designed to combine semantic adjacency with learning interests, and was used to quantify the semantic similarity of OLRs. In terms of knowledge structure analysis, Prasetya et al. [25] aimed to investigate the impact of extended scratch-build (ESB) concept mappings on student learning outcomes, including comprehension, mapping size and quality of knowledge structure. ESB is an extended open-ended technique that requires students to link pre-existing original concept maps to new additional maps on related material topics. ESB extends concept mappings by adding new propositions and linking them to previously existing mappings. In this way, it extends the concept mapping to enhance meaningful learning.

The existing research results can serve as reference for further in-depth research. However, there are still some problems to be solved, such as the lack of in-depth exploration for the internal structural characteristics of the organisation of knowledge networks constructed by expertise. There is also a lack of effective methods for constructing personalised knowledge networks oriented to students' cognitive states. This provides some opportunities for the research in this paper. In response, this article conducts an analysis of the categories and structures of expertise for students' cognitive states. Chapter 2 describes in detail the grey prediction algorithm for student cognitive state identification. Chapter 3 describes the categories of knowledge nodes within the expertise network for students' cognitive states, and then analyses the structure of the knowledge network from the perspectives of paths and statistical properties. The paper finally presents a method for analysing the knowledge flow of the expertise network. The experimental results validate the effectiveness of the proposed method.

2 Grey prediction of students' cognitive state

Figure 1 provides statistics on the influential elements of expertise cognition, with the core elements including the object of study, functional values, knowledge architecture and cognitive paths. As shown in the figure, the connotations of students' expertise cognition are interpreted as classifying, connecting, reinforcing and innovating expertise, i.e., selecting the cognitive paths that match their cognitive state to carry out the relevant research, while interpreting and analysing the categories of expertise to construct their knowledge network architecture.

This paper summarised the cognitive state of students' participation in the online learning process as the process shown in Figure 2. On the basis of known expertise, the network is associated with unknown expertise that meets the students' cognitive states. Then, it is internalised to reconstruct the expertise network, which is constantly optimised, modified while providing students with expertise that meets their current cognitive state as they continue to learn. Accordingly, the network is gradually rationalised and more science-based.

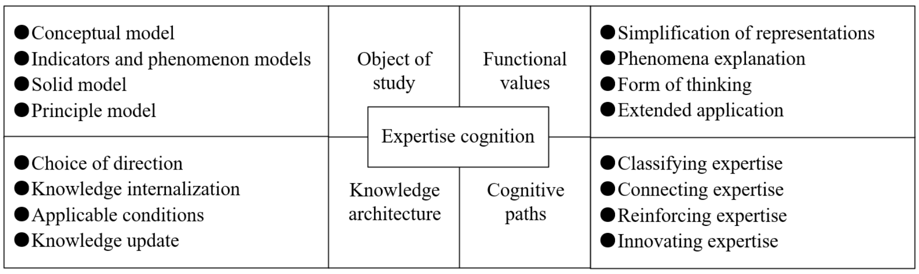

Fig. 1. Influential elements of expertise cognition

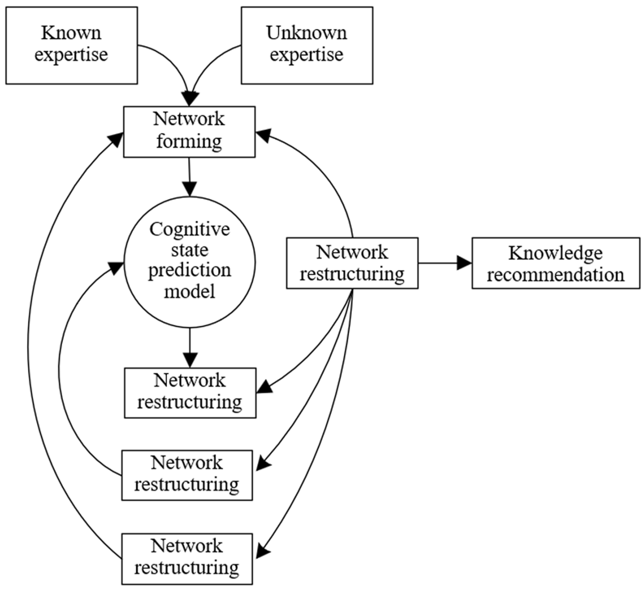

Fig. 2. Schematic diagram of the principle of cognitive state enhancement

This paper uses a grey prediction method to identify the cognitive states of students participating in online learning. The method further obtains the patterns of change in students' cognitive states by at first identifying the degree of development trends of the various factors influencing students' cognitive states and then generating the original influencing factor data for processing. Specifically, based on the obtained regular sequence of influencing factor data, the paper constructed a differential equation model for predicting the future evolution trend of students' cognitive states, which takes the form of a single-series first order linear differential equation model $GM(1,1)$.

Assuming that the non-negative canonical parameter is represented by μ and the penalty term is represented by $\lambda\sum_{j=1}^{p}\left|\beta_j\right|\mu\sum_{j=1}^{t}\left|\gamma_j\right|$, the traditional *Lasso* parameter estimate is defined through the following equation.

$$\hat{\gamma}(lasso) = \underset{\gamma}{argmin}^2\left\|b-\sum_{j=1}^{t}a_j\gamma_j\right\|^2+\mu\sum_{j=1}^{t}\left|\gamma_j\right| \tag{1}$$

To make the coefficients somewhat adaptive, weights are assigned to the different coefficients in this paper. Assuming weights $\hat{\omega}_j=\frac{1}{\left|\hat{\beta}_j\right|^{\gamma}}\hat{\theta}_j=\frac{1}{\left|\hat{\gamma}_j\right|^{\alpha}}$, ($\alpha$>0), j = 1, 2, …, t, the following equation gives the definition of an optimised *Lasso* parameter estimate.

$$\hat{\gamma}^{*(n)}(lasso) = \underset{\gamma}{argmin}^2\left\|b-\sum_{j=1}^{t}a_j\gamma_j\right\|^2+\mu_m\sum_{j=1}^{t}\hat{\theta}\left|\gamma_j\right| \tag{2}$$

Let each factor variable $A^{(0)}=\{A^{(0)}(i), i = 1, 2, \ldots, m\}$ be a non-negative monotonic raw data series, and the grey prediction model of students' cognitive states is constructed based on the following steps. Firstly, the cumulative sequence $A(1) = \{A(1)(l), l = 1, 2, \ldots, m\}$ is obtained by performing one accumulation on $A^{(0)}$. The following equation gives the first order linear differential equation constructed based on $A^{(1)}$.

$$\frac{dA^{(1)}}{dp}+\beta A^{(1)}=v \tag{3}$$

$$\hat{A}^{(1)}(l+1)=\left[\hat{A}^{(1)}(1)-\frac{\hat{v}}{\hat{\beta}}\right]o^{-\hat{\beta}l}+\frac{\hat{v}}{\hat{\beta}} \tag{4}$$

The single-series first order linear differential equation model is obtained as a cumulative quantity. Hence, after the cumulative reduction process, the resulting data $\hat{A}(1)(l+1)$ can be reduced to $\hat{A}(0)(l+1)$, the grey prediction model for the corresponding original sequence of influence factor data $A(0)$ is expressed as

$$\hat{A}^{(0)}(l+1)=(o^{-\hat{\beta}}-1)\left[A^{0}(m)-\frac{\hat{v}}{\hat{\beta}}\right]o^{-\hat{\beta}l} \tag{5}$$

The above modelling process leads to $\hat{A}(0)$ and the residuals. Make the variance of $A(0)$ and the residual sequence O denoted by R_1^2 and R_2^2 respectively, which results in the following

$$R_1^2=\frac{1}{m}\sum_{l=1}^{m}\left[a^{(0)}(l)-\bar{a}\right]^2 \tag{6}$$

$$R_2^2 = \frac{1}{m}\sum_{l=1}^{m}\left[o(l) - \bar{o}\right]^2 \tag{7}$$

Based on $\bar{x} = \frac{1}{n}\sum_{k=1}^{n} x^{(0)}(k)$, $\bar{e} = \frac{1}{n}\sum_{k=1}^{n} e(k)$, $\bar{a} = \frac{1}{m}\sum_{l=1}^{m} a^{(0)}(l)$, $\bar{o} = \frac{1}{m}\sum_{l=1}^{m} o(l)$, we could further calculate the posterior difference ratio $D = R_2/R_1$ and the small error probability $FR = FR\{|o(l) - \bar{o}| < 0.75R_1\}$.

3 Structural analysis of expertise networks for students' cognitive states

Traditional approaches to knowledge network structure analysis ignore the type and content of knowledge expertise and only analyse the network topology. In this paper, we first described the categories of knowledge nodes within the expertise network for students' cognitive states, and then analysed the knowledge network structure from two perspectives: pathways and statistical characteristics. Figure 3 shows a schematic diagram of the expertise network architecture.

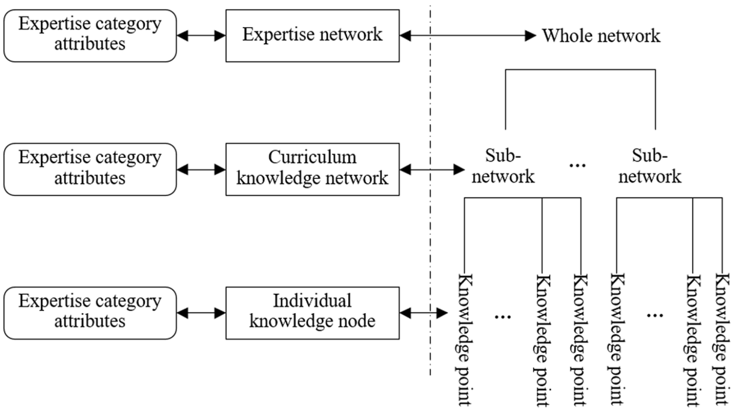

Fig. 3. Schematic diagram of the expertise network architecture

3.1 Description of expertise categories

The constructed expertise network is built based on n expertise nodes belonging to m majors. The expertise nodes are labelled as unknown or perceived by the students. As the nodes of the expertise network are majors, they cannot accurately characterise the knowledge flow between majors if they cannot be categorised as a specific major. The statistical results of expertise can be characterised by an $m \times m$ network adjacency matrix:

$$H' = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m,1} & x_{m,2} & \cdots & x_{m,m} \end{bmatrix} \tag{8}$$

Assume that the number of associations in which the j-th student's unknown expertise is associated by the i-th student's known expertise is denoted by x_{ij} ($i, j = 1, 2, \ldots, n$). To make it easy to construct connections between expertise and students, the main diagonal element of the matrix is made to be the number of associations of intra-expertise, often the maximum value of the elements of each row and column of the matrix. It can be assumed that the number of connections to intra-expertise is maximum for each major. Suppose that the intensity of knowledge flow from student-known major i to student-unknown major j is given by q_{ij} ($i, j = 1, 2, \ldots, m$), the matrix of knowledge relations between majors can be obtained by dividing each row of the matrix with x_{ij}:

$$H = [q_{ij}] = [x_{ij}/x_{ii}] \tag{9}$$

It can be shown that H can characterize the knowledge flow among majors, and the knowledge flow intensity can be measured by the set of network weights. Let the network $H = (U,P)$, the set of network expertise nodes is denoted by $U = \{u_1, u_2, u_3, \ldots, u_M\}$, the set of edges is denoted by $P = \{p_{ij}|i, j = 1, 2, \ldots, M\}$, and the number of nodes in the network is denoted by $M = |U|$. The number of edges connected to node u_i ($i = 1, 2, \ldots, M$) is characterized by its degree l_i, with the entry degree denoted by l_l^{in} and the exit degree denoted by l_i^{out}. The degree of entry is used to characterize the knowledge inflow relationship, while the degree of exit is used to characterize the knowledge outflow relationship. The weighted network can be represented by $H = (U,P,Q)$, where $Q = \{q_{ij}|i, j = 1, 2, \ldots, M\}$ and the weights of edge p_{ij} are denoted by q_{ij}.

3.2 Path-based analysis of the structure of expertise networks

In this paper, the network is structurally analysed from the perspective of the paths between the knowledge nodes of the expertise network for students' cognitive states. We selected the structural analysis indicators such as the average shortest path and diameter, the mediated nature of the network and the efficiency of the network for that structural analysis.

The length of the shortest path between nodes i and j in an expertise network is the number of connected edges on the shortest path, which is denoted by c_{ij}. The weights of the weighted network use the harmonic mean and are denoted by $c_{ij}^c = q_{il}q_{lj}/(q_{il}+q_{lj})$. The mean value of the shortest path between nodes in the expertise network is denoted by K. It is clear that in an expertise network for students' cognitive states, the amount of association between two expertise nodes will gradually become larger as the student's learning process progresses. Also, the possibility of knowledge flow increases gradually. Assuming that the set of connected edges on the shortest paths of nodes i and j is denoted by E_{ij}, the expression for the weights is

$$c_{ij}^{c} = 1/\sum_{q_E \in E_{ij}} \frac{1}{q_e} \tag{10}$$

The failure of a node may cause a change in the shortest distance through that node. In this paper, the number of shortest paths through a node is measured using a betweenness. Assuming that the number of shortest paths between nodes j and s is denoted by m_{js} and the number of shortest paths between j and s through node i is denoted by $m_{js}(i)$, then we defined:

$$y_i = \sum_{j,s=1, j\neq l}^{M} \frac{m_{js}(i)}{m_{js}} \tag{11}$$

The distance between knowledge nodes is an important factor affecting students' ability to perform expertise students and thus obtain cognitive state enhancement. In this paper, we characterized students' cognitive states enhancement ability through network efficiency. Assuming that the shortest path length between nodes i and j is represented by c_{ij}, we have the network efficiency calculation equation as follows:

$$G(H) = \frac{\sum_{i\neq j} g_{ij}}{m(m-1)} = \frac{1}{m(m-1)} \sum_{i\neq j} \frac{1}{c_{ij}} \tag{12}$$

Suppose the set of connected edges on the shortest path of nodes i and j is denoted by K_{ij} and the weights of any edge on the corresponding path are denoted by q_s. Introducing the weights, we have:

$$G(H) = \frac{1}{m(m-1)} \sum_{i\neq j} \left(\sum_{q_s \in K_{ij}} \frac{1}{q_s} \right) \tag{13}$$

Assuming that the expertise network after removing node u_i and its connecting edges is represented by $H\backslash u_i$, the network knowledge node efficiency is defined as below based on the network efficiency of the above equation:

$$G(u_i) = G(H) - G(H \backslash u_i) \tag{14}$$

3.3 Analysis of the structure of expertise networks based on statistical properties

In this paper, the network is structurally analysed from the perspective of knowledge node or edge statistics of the expertise network for students' cognitive states. We selected structural analysis indicators such as density and average degree of the network, degree distribution and relevance, hierarchy and circularity.

This paper quantifies the number of connectivity relationships between nodes in a network based on density and average degree. Assuming that the number of edges in a network of expertise is denoted by $|P|$, the density of the network is denoted by N, and the average degree of the network is denoted by $\langle l \rangle$, the value of N is obtained as below by comparing $|P|$ with the number of possible edges:

$$N = \frac{2|P|}{m(m-1)} \tag{15}$$

$\langle l \rangle$ is obtained by calculating the average value of degree l:

$$\langle l \rangle = \frac{1}{m}\sum_{i=1}^{m} l_i \tag{16}$$

Assume that the density of the expertise network H is denoted by N_H, the density of the strongly connected network W is denoted by N_W, and the average degree of H is denoted by $\langle l \rangle_H$. To characterize the distribution status of the node degrees of the network, this paper defines the node in-degree distribution $E(l^{in})$ and the out-degree distribution $E(l^{out})$ of H. $E(l^{in})$ and $E(l^{out})$ are usually represented by a cumulative degree distribution function to eliminate the effect of network size. Assuming that the probability distribution of expertise nodes with degree not less than l is represented by E_l, we have

$$E_l = \sum_{l'=l}^{\infty} E(l') \tag{17}$$

This paper quantifies the relevance of the network based on the *Pearson* correlation coefficient. Assuming that the number of edges of the network is represented by N_{ED} and the degree of the two nodes of the i-th edge is represented by j_i and l_i, we have the correlation coefficient calculation formula:

$$s = \frac{N_{ED}^{-1}\sum_i j_i l_i - \left[N_{ED}^{-1}\sum_i \frac{1}{2}\left(j_i + l_i\right)\right]^2}{N_{ED}^{-1}\sum_i \frac{1}{2}\left(j_i^2 + l_i^2\right) - \left[N_{ED}^{-1}\sum_i \frac{1}{2}\left(j_i + l_i\right)\right]^2} \tag{18}$$

The closeness of the connection between neighbours of an expertise node can be quantified by the node aggregation factor, and denoted by D_i. Assuming that the number of edges between neighbours of node i is denoted by K_i and the number of neighbouring nodes by l_i, the formula is:

$$D_i = \frac{2K}{l_i\ (l_i - 1)} \tag{19}$$

The aggregation coefficient of the whole expertise network is the mean of the aggregation coefficients of all nodes and satisfies $D = \sum D_i/M$. To better measure the relationship between the network nodes and other nodes, this paper introduces the node local loop coefficient metric. Suppose the degree of node i is denoted by l_i, any neighbouring node pair of node i is denoted by $\langle kn \rangle$, and the length of the minimum circle through node i and its neighbouring nodes k and n is denoted by R^i_{ln}, then we have:

$$g_i = \frac{2}{l_i\ (l_i - 1)} \sum_{\langle kn \rangle} \frac{1}{R^i_{kn}} \tag{20}$$

The recurrent coefficient of the whole expertise network is the mean of the local recurrent coefficients of the nodes, satisfying $G = \langle g_i \rangle$.

3.4 Knowledge flow analysis

Since the expertise network for students' cognitive states is considered as a directed weighted network. Assuming that the ratio of out- and in-degrees of nodes is represented by h_i, the ratio of outgoing and incoming weights is represented by h_i', the sum of outgoing and incoming weights of node i is represented by $\sum q_{ij}$ and $\sum q_{ji}$, and the position of nodes in the expertise network can be determined based on h_i and h_i', we have:

$$h_i = \frac{l_i^{out}}{l_i^{in}} \tag{21}$$

$$h_i' = \frac{\sum_{j \in \Psi} q_{ij}}{\sum_{j \in \Psi} q_{ji}} \tag{22}$$

4 Experimental results and analysis

Figure 4 shows the distribution of students' cognitive levels across the different online learning stages. As can be seen from the figure, the samples used to predict students' cognitive levels is mostly concentrated at Level 2, Level 3 and Level 4, which indicates that most students at different online learning stages are able to have a good understanding of the expertise they are studying and can explain some relevant common professional issues. Overall, the cognitive levels of students at different online learning stages generally conform to the overall distribution. The figure also indicates that students at all cognitive levels show an ability growth as they progress through the recommended stages of study.

The average betweenness of nodes in the expertise network was calculated to be 50.197, i.e., each expertise node can be considered to be a node on approximately 50.197 shortest paths. Table 1 shows the ranking of the course sub-network nodes in terms of their betweennesses, with the expertise nodes BE-1 to BE-10 playing a more important role in the expertise network in terms of knowledge connectivity compared to the other nodes.

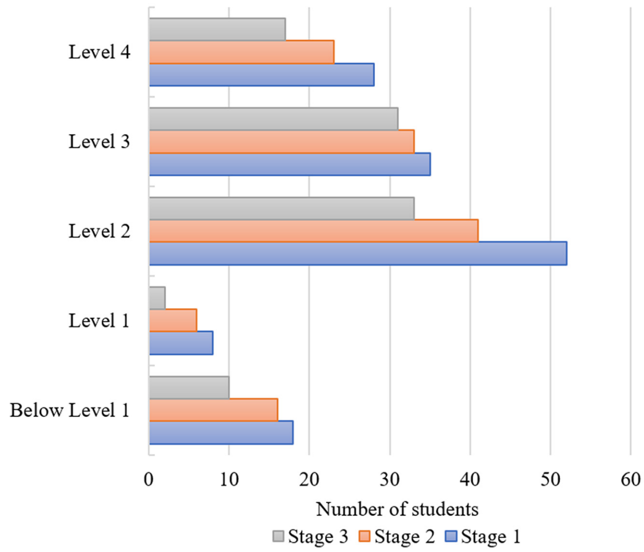

Fig. 4. Distribution of students' cognitive levels at different learning stages

Table 1. Ranking of betweennesses for course sub-network nodes

Sub-Network Node Number	Betweenness	Sub-Network Node Number	Betweenness
BE-1	362.591	BE-6	249.617
BE-2	285.427	BE-7	248.526
BE-3	271.963	BE-8	234.158
BE-4	265.681	BE-9	226.952
BE-5	253.627	BE-10	193.625

Table 2. Efficiency ranking of course sub-network nodes

Sub-Network Node Number	Efficiency	$G(u_i)/G(H)$
EF-1	0.00325	0.092
EF-2	0.00262	0.069
EF-3	0.00245	0.051
EF-4	0.00232	0.044
EF-5	0.00158	0.037

Table 3. Degree ranking of course sub-network nodes

Sub-Network Node Number	Degree	Sub-Network Node Number	Degree
DE-1	94	DE-6	65
DE-2	85	DE-7	53
DE-3	81	DE-8	49
DE-4	74	DE-9	44
DE-5	71	DE-10	21

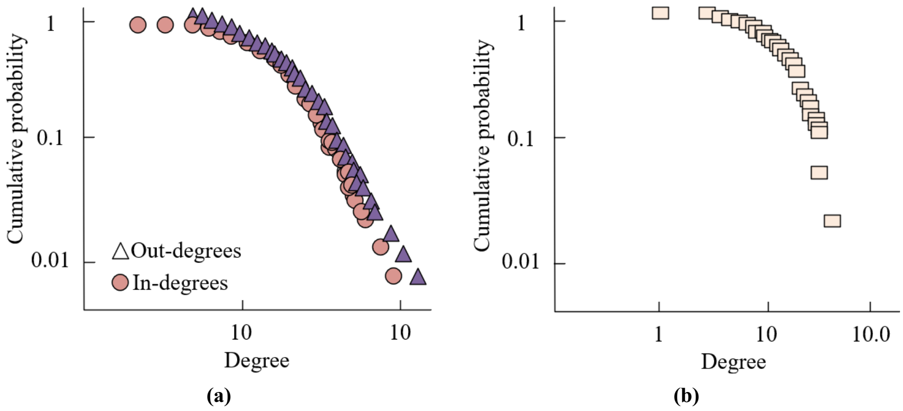

Fig. 5. Distribution of node degrees for different course sub-networks

Table 2 shows the efficiency ranking of the course sub-network nodes, with the third column showing the reduction ratio in the efficiency of the course sub-network after removing the expertise node u_i, i.e., the extent to which this expertise node affects the network efficiency of the expertise network. EF-1 has the highest network efficiency of 0.00325. The failure of this expertise node would result in a reduction in network efficiency of more than 9.2%. Table 3 shows the degree ranking of the course sub-network nodes. The expertise nodes in the table have a more frequent knowledge flow with other course sub-network nodes.

Figure 5a gives the cumulative distribution of out- and in-degrees for course sub-network 1 in a double logarithmic coordinate system. Figure 5b gives the cumulative degree distribution for course sub-network 2 in a double logarithmic coordinate system. From Figure 5, the out-degree and in-degree distributions of course sub-network 1 and the tail of the degree distribution of course sub-network 2 can be judged to obey the power-law distribution. Analysis reveals that the out-degree of course sub-network 1 obeys a power-law distribution with an exponent of 1.862, the in-degree obeys a power-law distribution with an exponent of 2.334, and the degree distribution of course sub-network 2 obeys a power-law distribution with an exponent of 2.077. The above distribution results indicate that some course sub-networks in the expertise network have very large out- or in-degrees with other course sub-networks, i.e., there is more frequent knowledge flow with each other, and there are also course sub-networks that only have knowledge exchange with a few course sub-networks. Course sub-network 2 is a strongly connected network, and the results of the inter-degree correlation analysis are given in Figure 6. As can be seen from the figure, the interrelationships between the nodes in course sub-network 2 are more obvious.

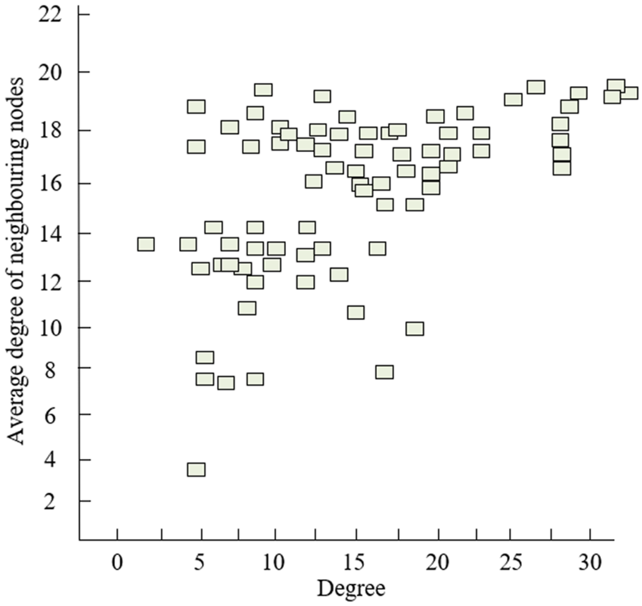

Fig. 6. Inter-degree correlation of the course sub-network

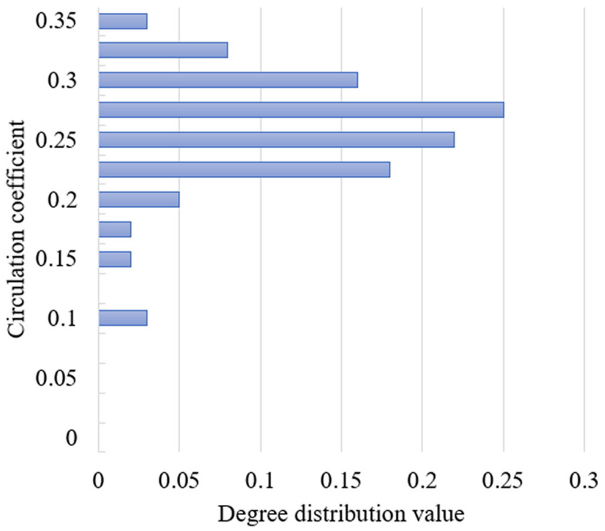

Fig. 7. Distribution of local circulation coefficients for the course sub-network

Figure 7 illustrates the distribution of local circulation coefficients for the course sub-network. The figure reveals that the local loop coefficients of the nodes in the expertise network take values in the range of [0.1,0.35], with over 80% of the nodes in the range of [0.2,0.35], while the loop coefficient of the expertise network is 0.291. This verifies that the constructed expertise network contains a large number of sub-networks and loops.

5 Conclusion

This paper analyses the categories and structures of expertise for students' cognitive states, and presents in detail a grey prediction algorithm to identify students' cognitive states. Then, the paper presents a typological description of the knowledge nodes in the expertise network for students' cognitive states, and analyses the knowledge network structure from the perspectives of paths and statistical properties. After that, the paper gives a method for analysing the knowledge flow of the expertise network. The experimental results present the distribution of students' cognitive levels at different learning stages, while ranking the course sub-network nodes according to their betweenness, efficiency and degree, along with the corresponding analysis results. The paper also presents the cumulative distribution of out- and in-degrees of the course sub-networks in a double logarithmic coordinate system. The distribution shows that some of the course sub-networks in the expertise network have very large out- or in-degrees with other course sub-networks, i.e., there is a more frequent knowledge flow with each other. By presenting the distribution of the local loop coefficients of the course sub-networks, the paper verifies that the constructed expertise network contains a large number of sub-networks and loops.

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Article submitted 2022-09-30. Resubmitted 2022-12-06. Final acceptance 2022-12-07. Final version published as submitted by the authors.