Evaluation of Improvement of Information Teaching Ability Based on Complex Online Network

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The evaluation of the improvement of information teaching ability (ITA) helps teachers to proactively learn advanced information teaching techniques and to realize innovative information teaching. The relevant studies mainly focus on the theoretical level and rarely deal with the growth of teachers through learning. Therefore, this paper presents an evaluation method for ITA improvement based on complex online network. Firstly, an analysis framework was established for the activity of the ITA improvement network (ITAIN) and used to measure the ITAIN activity under the learning condition of complex online network. Following the evaluation strategy of preference ranking organization method for enrichment evaluation (PROMETHEE), the author constructed an evaluation model for the improvement of ITA and an evaluation index system (EIS) of five primary indices. The proposed model was proved effective through experiments.

1. Introduction

In the age of Internet and information, there is a growing demand for talents with comprehensive quality, which changes the direction of talent training [1, 2]. To keep abreast with the times and improve their ability of professional teaching, modern teachers need to actively integrate information teaching technology into daily teaching [3–7]. Information teaching requires a complete structure of professional knowledge, an advanced teaching concept, and mature practical skills. All these are the abilities to diversify classroom teaching. If a teacher wants to improve his/her information teaching ability (ITA), he/she can learn various resources online [8–13]. The evaluation of the ITA improvement helps teachers to proactively learn advanced information teaching techniques and to realize innovative information teaching.

Gong [14] found that the teachers in rural schools are neither enthusiastic about nor capable of information teaching because the equipment is rarely used and difficult to repair and explored the factors affecting the ITA of these teachers from three aspects, namely, students, school, and government. Considering the need of information teaching training for college teachers, Claro et al. [15] designed and implemented an information training strategy, which includes five phases such as incubation, alliance, action, commemoration, and dispersion, and summarized the change law of ITA of the trained teachers.

The knowledge framework of technique-driven subject teaching provides a brand-new cultivation path for improving the ITA of teachers [16, 17]. Liu [18] summarized the problems of new teachers of specialized courses as poor knowledge integration, course integration, and content rationality and renovated multiple aspects of the ITA of these teachers, namely, training scheme preparation, course teaching planning, and appraisal method.

The innovative integration of information technology in course teaching is an important attribute of modern teaching in colleges [19, 20]. The existing studies mainly focus on the connotations, framework, and development trend of ITA. Romero-Rodriguez et al. [21] creatively took the innovative ITA as the object, analyzed the factors affecting the ability and their action mechanism, and constructed a structural equation model (SEM) for evaluating the ability based on Amos. Dan [22] discussed the correlations between the four influencing factors for the innovative ITA of college teachers.
and sorted out their direct promoting and inhibiting effects. The four factors are the application ability of information technology, the knowledge of information teaching, the awareness of information teaching, and teachers’ satisfaction of information construction.

The previous studies on ITA improvement have laid a basis for the training model and evaluation of this ability. But most of them emphasize on value creation, quality evaluation, existing problems, and solutions. The relevant studies mainly focus on the theoretical level and rarely deal with the growth of teachers through learning.

Drawing on the previous research of complex networks, this paper proposes an evaluation method for ITA improvement, which carries the features of the times. The main contents cover the following aspects: (1) building an analysis framework for the activity of the ITA improvement network (ITAIN) and analyzing the activity of ITAIN under the learning condition of complex online network; (2) setting up an evaluation model for ITA improvement under the evaluation strategy of preference ranking organization method for enrichment evaluation (PROMETHEE); (3) constructing five evaluation networks based on the proposed evaluation index system (EIS), namely, professional foundation of information teaching, design ability of information teaching, implementation and monitoring ability of information teaching, evaluation ability of information teaching, and research ability of information teaching; and (4) proving the effectiveness of the proposed model through experiments.

2. ITAIN Activity

This paper measures the improvement of ITA with the node connectivity, closeness, and mean path length of online network, as well as two centrality indices: betweenness and clustering coefficient. Figure 1 shows the analysis framework of ITAIN activity.

In the complex online education network, there are lots of intricately connected platforms and resources for the learning and ITA training of teachers. Among the platform and resource clusters, each instance that promotes the ITA improvement was viewed as a node in the network. Then, the promoting and inhibiting relationships between the instances were treated as the edges between nodes. Each edge was weighed according to the importance of the relationship between the instances. On this basis, the activity of ITAIN was evaluated under the learning condition of complex online network. The above indices were quantified in the following manner.

Let $N$ be the number of nodes in the network and $s_{ab}$ be the distance from node $a$ to node $b$. Then, the node connectivity of the online network that characterizes the correlation between instances can be calculated by

$$G(a) = \sum_{b=1}^{N} s_{ab}.$$  (1)

Formula (1) shows that, in the complex online network, the node connectivity between nodes $a$ and $b$ is 1, if the two nodes are directly connected; the connectivity is 0, otherwise. In this paper, the ITA improvement of teachers is measured from two aspects: the instances of learning activities and the instances of improvement support. Among the former instances, the more the training platforms and effective training resources, the greater the improvement of the ITA. The rising ITA gives teachers more rights and chances to acquire more training opportunities and resources. As a result, the ITA of the teachers will improve continuously.

Let $N$ be the number of nodes in the online network and $s_{ab}$ be the shortest distance from node $a$ to node $b$. Then, the closeness $GM(a)$ of node $a$, which measures how convenient it is for the node to communicate with other nodes in the network, can be calculated by

$$GM(a) = \frac{1}{\sum_{b=1}^{N} s_{ab}}.$$  (2)

Formula (2) shows that, unlike the node connectivity $G(a)$ reflecting the basic connection between instances, the closeness $GM(a)$ of network nodes reveals the number of intermediate nodes on the path between a node and another node. To a certain extent, this index shows the independence of the promoting and inhibiting effects between instances. The closeness characterizes the difficulty/easiness of implementing ITA improvement activities in the network. Its value mirrors the size of teachers’ ITA.

In the online network, the transmission speed of various resources (e.g., knowledge and research results) depends on the mean path length $K$ of the network:

$$K = \frac{1}{(1/2)N(N + 1)} \sum_{a \neq b} s_{ab}.$$  (3)

Formula (3) shows that the $K$ value reflects the number of intermediate nodes that a node needs to pass through to share information/knowledge effectively or connect with another node in the network. The minimum $K$ value is the distance from the node to itself: 0. In this paper, the path length of ITA improvement is measured based on the ability improvement cost and speed, the teaching hours of training platforms during skill spillover, and the number of visits to resources.

Let $N_{lc}(a)$ be the number of shortest paths in the network of node $a$ and $N_{hc}$ be the number of shortest paths linking up node $b$ and node $c$ in the network. Then, the betweenness $IP(a)$, which reflects the importance of a resource to ITA improvement, can be calculated by

$$IP(a) = \sum_{b \neq c} \frac{N_{lc}(a)}{N_{hc}}.$$  (4)

Formula (4) shows that $IP(a)$ describes the number of times a node is traversed during the ITA improvement activities, reflecting the influence of the node on ITA improvement among the shortest paths. If the $IP(a)$ is high, the instance must boast enough necessary elements for ITA improvement activities. Here, the betweenness of the complex online network for ITA improvement is measured
in terms of platforms, resource conditions, and policy environment. The instances of the complex online network can fully play their roles, if they are authentic training platforms and core teaching resources, supported by the policy environment.

In the complex online network, it is assumed that node \( b \) is connected with node \( a \) and node \( u \), respectively. Then, it is very likely that node \( a \) is connected with node \( u \). Suppose the subnetwork of node \( a \) contains \( N_a \) nodes and \( F_a \) edges, and the maximum number of possible edges is \( GN_a^2 \), that is, \( N_a(N_a-1)/2 \). Then, the node clustering effect in the network can be characterized by the clustering coefficient:

\[
IC(a) = \frac{F_a}{GN_a^2} = \frac{2F_a}{N_a(N_a-1)} \tag{5}
\]

In the complex online network of ITA training, \( IC(a) \) reflects the cohesion between network nodes and the tightness of the promoting and inhibiting relationships between instances in the cluster. This paper measures the clustering ability of instances by platform scale, resource scope, education strategies, and teaching methods.

3. Model Construction

3.1. PROMETHEE Evaluation Strategy. The traditional evaluation method does not fully consider the fuzziness and stochasticity of the evaluation process. The complex structure of online education network cannot be directly described by simple linear relationships. To solve the problem, this paper introduces the cloud model theory to the traditional multi-objective decision making and evaluation, aiming to evaluate the ITA improvement of teachers. Comparative calculation and analysis were performed to evaluate the ITA activity more rigorously and scientifically.

Let \( IC_1, IC_2, \ldots, IC_N \) be \( N \) clusters of instances that promote ITA improvement; \( GI_1, GI_2, \ldots, GI_M \) be the \( M \) indices of each instance cluster; \( AV_{ij} \) be attribute \( l \) of index \( j \) in instance cluster \( i \); and \( \theta=(\theta_1, \theta_2, \ldots, \theta_j) \) be the weight of an index in its instance cluster. Then, the ITA improvement can be evaluated in the following steps based on complex online network.

**Step 1.** Convert each attribute of instance cluster indices to the cloud.

The expectation \( EXP \) of each attribute of index \( j \) in instance cluster \( i \) can be calculated by

\[
EXP_{ij} = \frac{\sum_{l=1}^{K} AV_{ijkl}}{K}. \tag{6}
\]

The entropy \( ENT \) can be calculated by

\[
ENT_{ij} = \frac{1}{K} \sum_{l=1}^{K} \left| AV_{ijl} - E_{ij} \right|. \tag{7}
\]
The hyperentropy $H_{\text{ENT}}$ can be calculated by
\[
H_{\text{ENT}} = D^2 = \frac{K}{K-1} \sum_{i=1}^{K} (G_{ij} - \text{EXP}_i)^2 .
\] (8)

**Step 2.** Define the comparison rules for each attribute of indices of instance clusters.

Let $GI_j(\text{EXP}_i, \text{ENT}_i, H_{\text{ENT}})$ be the cloud attribute of instance cluster $IC_i$ under index $GI_j$, $s_j(\text{IC}_i, IC_g) = s_j(\text{EXP}_i, \text{ENT}_i, H_{\text{ENT}})_j$ be the cloud attribute difference between two instance clusters under index $GI_j$, and $GI_j(\text{EXP}_j, \text{ENT}_j, H_{\text{ENT}})$ be the cloud attribute of instance cluster $IC_g$. Then, the expectation $\text{EXP}$, entropy $\text{ENT}$, and hyperentropy $H_{\text{ENT}}$ between the two instance clusters can be compared by the following rules:

1. For $\text{EXP}$, when index $GI_j$ needs to be maximized, if $\text{EXP}_j > \text{EXP}_g$, then $s_j(\text{IC}_i, IC_g) > 0$; if $\text{EXP}_j \leq \text{EXP}_g$, then $s_j(\text{IC}_i, IC_g) = 0$; when index $GI_j$ needs to be minimized, if $\text{EXP}_j < \text{EXP}_g$, then $s_j(\text{IC}_i, IC_g) > 0$; if $\text{EXP}_j \geq \text{EXP}_g$, then $s_j(\text{IC}_i, IC_g) = 0$.

2. For $\text{ENT}$, if $\text{ENT}_j \geq \text{ENT}_g$, then $s_j(\text{IC}_i, IC_g) = 0$; if $\text{ENT}_j < \text{ENT}_g$, then $s_j(\text{IC}_i, IC_g) > 0$.

3. For $H_{\text{ENT}}$, if $H_{\text{ENT}}_j \geq H_{\text{ENT}}_g$, then $s_j(\text{IC}_i, IC_g) = 0$; if $H_{\text{ENT}}_j < H_{\text{ENT}}_g$, then $s_j(\text{IC}_i, IC_g) > 0$.

**Step 3.** Convert the preference function to the cloud. Unlike other preference functions, Gaussian preference function changes nonlinearly and better suits the actual decision-making environment. Therefore, this paper chooses Gaussian preference function to transform the attribute cloud of the evaluation indices for each instance cluster.

Let $W(\text{IC}_i, IC_g) = W(\text{EXP}_i, \text{ENT}_i, H_{\text{ENT}}_i)$ be the preference index indicating that the cloud attribute $GI_j(\text{EXP}_i, \text{ENT}_i, H_{\text{ENT}})$ of instance cluster $IC_i$ is better than that of $GI_j(\text{EXP}_g, \text{ENT}_g, H_{\text{ENT}})$ of instance cluster $IC_g$ under index $GI_j$ and $\sigma$ be the threshold of the Gaussian function. Then, the cloud preference index $\Omega(\text{IC}_i, IC_g)$, i.e., the cloud preference index $\Omega(\text{IC}_i, IC_g)$, can be calculated by

\[
\Omega(\text{IC}_i, IC_g) = \frac{\sum_{j=1}^{N} \theta_j W(\text{IC}_i, IC_g)}{\sum_{j=1}^{N} \theta_j} = \left[ \theta_1 + \theta_2 + \cdots + \theta_J \right]^T \begin{bmatrix} \text{EXP}_{1ig} & \text{ENT}_{1ig} & H_{\text{ENT}}_{1ig} \\ \vdots & \vdots & \vdots \\ \text{EXP}_{jig} & \text{ENT}_{jig} & H_{\text{ENT}}_{jig} \end{bmatrix} \]
\[
= \begin{pmatrix} \theta_1 \text{EXP}_{1ig} + \theta_2 \text{EXP}_{2ig} + \cdots + \theta_J \text{EXP}_{jig} \\ \sqrt{\left(\theta_1 \text{ENT}_{1ig}\right)^2 + \left(\theta_2 \text{ENT}_{2ig}\right)^2 + \cdots + \left(\theta_J \text{ENT}_{jig}\right)^2} \\ \sqrt{\left(\theta_1 H_{\text{ENT}}_{1ig}\right)^2 + \left(\theta_2 H_{\text{ENT}}_{2ig}\right)^2 + \cdots + \left(\theta_J H_{\text{ENT}}_{jig}\right)^2} \end{pmatrix}^T 
\]

\[
= \left( \text{EXP}_{1ig}, \text{ENT}_{1ig}, H_{\text{ENT}}_{1ig} \right) .
\]
Step 4. Compute cloud outflow, cloud inflow, and cloud net flow.

The superiority of instance cluster \( IC_i \) over other instance clusters in learning activity can be measured by cloud outflow \( \Psi_p( IC_i ) \):

\[
\Psi_p( IC_i ) = \frac{1}{N-1} \sum_{g=1}^{N} \Omega( IC_i, IC_g )
\]

\[
= \frac{1}{N-1} \begin{pmatrix}
\exp_{\Omega,1} + \exp_{\Omega,2} + \cdots + \exp_{\Omega,N} \\
\sqrt{\text{ENT}^2_{\Omega,1} + \text{ENT}^2_{\Omega,2} + \cdots + \text{ENT}^2_{\Omega,N}} \\
\sqrt{\text{HENT}^2_{\Omega,1} + \text{HENT}^2_{\Omega,2} + \cdots + \text{HENT}^2_{\Omega,N}} \\
\end{pmatrix}^T
\]

(11)

The inferiority of instance cluster \( IC_i \) over other instance clusters in learning activity can be measured by cloud inflow \( \Psi_I( IC_i ) \):

\[
\Psi_I( IC_i ) = \frac{1}{N-1} \sum_{g=1}^{N} \Omega( IC_g, IC_i )
\]

\[
= \frac{1}{N-1} \begin{pmatrix}
\exp_{\Omega,1} + \exp_{\Omega,2} + \cdots + \exp_{\Omega,N} \\
\sqrt{\text{ENT}^2_{\Omega,1} + \text{ENT}^2_{\Omega,2} + \cdots + \text{ENT}^2_{\Omega,N}} \\
\sqrt{\text{HENT}^2_{\Omega,1} + \text{HENT}^2_{\Omega,2} + \cdots + \text{HENT}^2_{\Omega,N}} \\
\end{pmatrix}^T
\]

(12)

\[
= (\exp_{\Omega}, \text{ENT}_{\Omega}, \text{HENT}_{\Omega}).
\]
3.2. Index Weighting. Primary indices: \( IT = \{ IT_1, IT_2, IT_3, IT_4, IT_5 \} = \{ \text{professional foundation of information teaching, design ability of information teaching, implementation and monitoring ability of information teaching, evaluation ability of information teaching, research ability of information teaching} \} \)

Secondary indices: \( IT_1 = \{ IT_{11}, IT_{12}, IT_{13} \} = \{ \text{awareness and attitude, basic knowledge, basic skills} \} \)

\( IT_2 = \{ IT_{21}, IT_{22}, IT_{23}, IT_{24} \} = \{ \text{teaching objectives and planning ability, student condition analysis ability, teaching strategy design ability, learning situation design ability} \} \)

\( IT_3 = \{ IT_{31}, IT_{32}, IT_{33} \} = \{ \text{collaboration ability, organization and management ability, control and regulation ability} \} \)

\( IT_4 = \{ IT_{41}, IT_{42}, IT_{43}, IT_{44} \} = \{ \text{ability to set appraisal rules, ability to utilize various means of information teaching, ability to provide real-time feedbacks with information technology, ability to visualize evaluation results} \} \)

\( IT_5 = \{ IT_{51}, IT_{52}, IT_{53} \} = \{ \text{teaching reflection ability, sustainable development ability of information teaching, innovation ability of information teaching} \} \)

Figures 2 and 3 present the evaluation networks of professional foundation of information teaching and design ability of information teaching, respectively. The two networks have 3 and 5 connected components and 26 and 29 evaluation indices, respectively. It can be intuitively inferred that the ITA improvement promotes both professional foundation of information teaching and design ability of information teaching, and the relevant indices are closely correlated, indicating a certain promoting effect.

Figures 4–6 present the evaluation networks of implementation and monitoring ability of information teaching, evaluation ability of information teaching, and research ability of information teaching, respectively. The three networks have 3, 4, and 4 connected components and 27, 24, and 22 evaluation indices, respectively. Similarly, the ITA improvement promotes implementation and monitoring ability of information teaching, evaluation ability of information teaching, and research ability of information teaching.

In the ITA evaluation system, the indices were treated as the edges between the nodes of the complex online network, and the connected instances were linked up as network nodes, forming reasonable ITA improvement paths. Based on the importance of instance nodes in the complex online network, the authors calculated and normalized the node degree, closeness centrality, and node centrality of each index, derived the net flows of all indices according to the normalized results, and further obtained the weight of each index. The specific steps are as follows:

Step 1. Normalize index attributes of complex online network.

The node degree \( \text{DE}_a \) of an N-node complex online network is smaller than \( N - 1 \). The node degree can be normalized as

\[
G_v(u_a) = \frac{\text{DE}_a}{N - 1}
\]

In the N-node complex online network, the sum of the shortest paths between any node and other nodes is \( \sum_{j=1}^{N} s_{ij} \), which is greater than \( N - 1 \). Then, the closeness centrality can be normalized as

\[
NE_v(u_a) = \frac{N - 1}{\sum_{b=1}^{N} s_{ab}}
\]

The betweenness of node \( u_a \) can be described by

\[
IP_z(u_a) = \sum_{bc} h_{bc}(i)/h_{bc}
\]

and normalized as

\[
IP_z(u_a) = \frac{2IP_z(u_a)}{(N - 1)(N - 2)}
\]
Step 2. Select the preference function.
Let $L_M$ be the network attributes of $M$ indices $G_I = \{G_{I_1}, G_{I_2}, \ldots, G_{I_M}\}$ and $L_1, L_2,$ and $L_3$ be the node degree, betweenness, and closeness centrality, respectively. The index attribute $G_{IM}$ of $G_I$ under $L_M$ can be obtained by evaluating ITA improvement against $L_M$. Suppose $(G_{I_1}, G_{I_2})$ is the Gaussian preference function of index $G_{I_1}$ relative to index $G_{I_2}$ under $L_M$ and $G_{IM} - G_{JM} = \rho M(G_{I_1}, G_{I_2})$, which is denoted as $\rho$. Then,

$$U(\rho) = \begin{cases} 
0, & \rho \leq 0, \\
1 - e^{-\rho^2/2\sigma^2}, & \rho > 0.
\end{cases}$$

Step 3. Calculate the multi-index preference order index of evaluation indices.

The superiority of index $G_{I_1}$ over index $G_{I_2}$ can be characterized by the preference order index:

$$\prod (G_{I_1}, G_{I_2}) = \prod_{M=1}^{3} U_M(G_{I_1}, G_{I_2}).$$

Step 4. Calculate outflow, inflow, and net flow of evaluation indices.

The superiority of index $G_{I_1}$ over other indices can be characterized by the outflow:

$$\Gamma_p(G_{I_1}) = \sum_{j=1}^{M} \prod(G_{I_1}, G_{I_j}).$$

The inferiority of index $G_{I_1}$ over other indices can be characterized by the inflow:

$$\Gamma_i(G_{I_1}) = \sum_{j=1}^{M} \prod(G_{I_j}, G_{I_1}).$$

To a certain extent, the preference order of index $G_{I_1}$ can be reflected by the net flow:

$$\Gamma(G_{I_1}) = \Gamma_p(G_{I_1}) - \Gamma_i(G_{I_1}).$$

Step 5. Calculate the weights of evaluation indices.
The indices can be ranked by the net flow obtained by formula (21). Then, the relative flow $\Delta t_i$ of each index, i.e., the difference between net flow of each index and minimum net flow, can be calculated by

$$\Delta t_i = \Gamma(G_{I_i}) - \min \Gamma(G_{I_i}).$$

The weight of each index can be obtained by normalizing $\Delta t_i$.

$$\theta_i = \frac{U_i}{\sum_{i=1}^{M} U_i}.$$

4. Experiments and Result Analysis

The distribution of node connectivity is an important global index in the complex network measuring system for ITA improvement. Figure 7 presents the node connectivity distributions of three instance clusters: platform instance cluster, resource instance cluster, and hybrid instance cluster. The former two are clusters composed of a single type of simply connected instances, while the latter is a complex network consisting of multiple instances. In the platform instance cluster, each instance only shares information/knowledge with an average of two nearby instances, while the instances in the cluster of network resources share information or knowledge with an average of 14 nearby instances. Therefore, quite a lot of network resources can share information or knowledge via potential paths.

Figure 8 compares the network closeness distributions of different instance clusters. The instances are sparsely connected in the single-instance simple network, while the instances are closely connected in the multi-instance complex network.

To confirm the reliability of the index weights, this paper summarizes and analyzes the reliability and validity of ITA
improvement indices. Firstly, the factor loadings and reliability coefficients of the primary and secondary indices were computed on SPSS and Amos. The results in Table 1 show that Cronbach’s alpha of the entire index system was 0.911 and that of each dimension under each primary index was greater than 0.9. Taking IT, for example, for all its secondary indices, Cronbach’s alphas were greater than 0.7, the mean variances were greater than 0.7, and the composite reliabilities were greater than 0.7. This means that the proposed evaluation indices are highly reliable and valid.

Then, the node degree, betweenness, and closeness centrality of each primary index were calculated on
MATLAB (Table 2). Taking the results as evaluation criteria, the network attributes of secondary indices were compared to obtain the net flow of each secondary index (Table 3).

As shown in Table 3, collaboration ability $IT_{31}$ and ability to set appraisal rules $IT_{41}$ had relatively low net flows, indicating the low priority of the two indices in the ITA index system. That is, $IT_{31}$ and $IT_{41}$ in the EIS are not top considerations of the teachers during the improvement of their ITA. After that, the net flows of other indices relative to $IT_{31}$ and $IT_{41}$ were computed and normalized and used to derive the weights of secondary indices (Table 3).
Table 1: Reliability and validity of ITA improvement indices.

| Primary indices | Secondary indices | Factor loading | Reliability coefficient | Measuring error | Cronbach’s alpha | Composite reliability | Mean variance |
|-----------------|-------------------|----------------|-------------------------|-----------------|-------------------|-----------------------|--------------|
| $IT_1$          | $IT_{11}$         | 0.715          | 0.542                   | 0.451           | 0.863             | 0.859                 | 0.562        |
|                 | $IT_{12}$         | 0.762          | 0.539                   | 0.432           | 0.795             | 0.792                 | 0.556        |
|                 | $IT_{13}$         | 0.793          | 0.631                   | 0.379           | 0.786             | 0.786                 | 0.567        |
| $IT_2$          | $IT_{21}$         | 0.849          | 0.736                   | 0.294           | 0.761             | 0.765                 | 0.534        |
|                 | $IT_{22}$         | 0.537          | 0.279                   | 0.726           | 0.762             | 0.765                 | 0.534        |
|                 | $IT_{23}$         | 0.724          | 0.652                   | 0.378           | 0.762             | 0.765                 | 0.534        |
|                 | $IT_{24}$         | 0.624          | 0.554                   | 0.518           | 0.762             | 0.765                 | 0.534        |
| $IT_3$          | $IT_{31}$         | 0.931          | 0.812                   | 0.189           | 0.764             | 0.767                 | 0.567        |
|                 | $IT_{32}$         | 0.556          | 0.309                   | 0.632           | 0.764             | 0.767                 | 0.567        |
|                 | $IT_{33}$         | 0.746          | 0.537                   | 0.456           | 0.764             | 0.767                 | 0.567        |
| $IT_4$          | $IT_{41}$         | 0.851          | 0.772                   | 0.218           | 0.811             | 0.747                 | 0.521        |
|                 | $IT_{42}$         | 0.517          | 0.235                   | 0.753           | 0.811             | 0.747                 | 0.521        |
|                 | $IT_{43}$         | 0.748          | 0.628                   | 0.311           | 0.811             | 0.747                 | 0.521        |
|                 | $IT_{44}$         | 0.618          | 0.548                   | 0.599           | 0.811             | 0.747                 | 0.521        |
| $IT_5$          | $IT_{51}$         | 0.917          | 0.847                   | 0.187           | 0.723             | 0.776                 | 0.579        |
|                 | $IT_{52}$         | 0.729          | 0.518                   | 0.422           | 0.723             | 0.776                 | 0.579        |
|                 | $IT_{53}$         | 0.751          | 0.711                   | 0.549           | 0.723             | 0.776                 | 0.579        |

Table 2: Network attributes of primary indices.

| Evaluation indices | Node degree | Betweenness | Closeness centrality |
|--------------------|-------------|-------------|----------------------|
| $IT_1$             | 0.56        | 0.11        | 0.72                 |
| $IT_2$             | 0.27        | 0.06        | 0.79                 |
| $IT_3$             | 0.23        | 0.01        | 0.52                 |
| $IT_4$             | 0.23        | 0.01        | 0.56                 |
| $IT_5$             | 0.25        | 0.01        | 0.59                 |

Figure 8: Network closeness distributions of different instance clusters. (a) Single-instance simple network. (b) Multi-instance complex network.
5. Conclusions

This paper presents a novel evaluation method for ITA improvement based on complex online network. After setting up the analysis framework, ITAIN activity was analyzed from the perspectives of node connectivity, clustering coefficient, mean path length, and betweenness of the online network. Under the evaluation strategy of PROMETHEE, the author established an evaluation model for ITA improvement and built five primary index evaluation networks: professional foundation of information teaching, design ability of information teaching, implementation and monitoring ability of information teaching, evaluation ability of information teaching, and research ability of information teaching. Through experiments, the distribution of node connectivity and closeness in networks of different instance clusters were obtained, which reflects that the instances in multi-instance complex network have closer connections than those in single-instance simple network. Further, the indices of teachers’ ITA were subject to reliability and validity test, and the network attributes of primary indices and the net flows of secondary indices were calculated. The relevant results demonstrate the high reliability and good validity of the proposed indices.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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