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Article

Strategic Planning for the Sustainable Development of Educational Enterprises: Integrating Optimization Models and Creating Innovative Learning Environments

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Abstract: Due to market fluctuations caused by changes in policies regarding extracurricular education and training, education and training companies face significant development pressures. This paper collects teaching activity data from Z Education and Training Company and applies complex network theory to evaluate the course feature network by analyzing the average path length, clustering coefficient, and degree distribution of a bipartite network. Additionally, the K-means algorithm and correlation analysis methods are used to analyze learning environment data and optimize learning environment pathways. The results indicate that the average path length of the complex network for Z Education and Training Company is 2.471, with the shortest path being 1 or 7, and a clustering coefficient of 0.211. The overall network exhibits small-world scale characteristics, while the user behavior network of the education company follows a power-law distribution. Furthermore, characteristics such as the difficulty level and mastery of knowledge points provide guidance for optimizing learning environment paths. Education companies should base their strategic adjustments and optimizations on the learning situation data of their own students' participation in teaching activities.

Keywords: educational enterprises; strategic planning; complex network theory; learning environment data

1. Introduction

With the rapid socio-economic development of China, the education sector has become increasingly important to the national economy [1-2]. However, a large number of education companies currently lack clear, scientific, and long-term strategic plans, let alone sustainable development strategies or effective strategic implementation systems. With the exception of a few leading education enterprises, the majority have not established unique business models; instead, they tend to simply imitate and replicate existing, proven practices. For example, schools and training institutions primarily adopt a model focused on hiring renowned teachers or engaging in intensive test-prep drills to improve students' exam scores [3-4]. How education enterprises can formulate and implement differentiated strategies to drive socioeconomic development and achieve sustainable growth is an urgent issue that must be addressed [5-6]. To adapt to the development needs of the new era, educational enterprises urgently need to achieve breakthroughs on two fronts: integrating optimization models into sustainable development strategy planning and constructing innovative learning environments.

By integrating optimization models and combining multi-dimensional analyses—such as systematic learning and educational service innovation—educational enterprises can develop systematic strategic decision-making tools to drive precise development within an education industry characterized by complexity, diversity, and intense competition. Regarding the learning environment, in the current digital context, educational enterprises can leverage digital technologies to innovatively construct learning environments [7-8]. Compared to traditional learning environments, digital learning environments provide learners with rich and diverse resources, breaking through the constraints of time and space [9-10].

Data on the daily teaching activities of educational enterprises serves as a crucial foundation for their sustainable strategic development. This paper collects educational data from the target enterprise, applies complex network theory to characterize the data features of the target educational enterprise, and establishes a BA scale-free bimodal network model. It calculates the average path length, clustering coefficient, and degree distribution to better evaluate the overall characteristics of the teaching network. To optimize learning environment pathways, cluster analysis methods are employed to aggregate the behavioral characteristics of the target educational enterprise's students. Combined with Spearman's correlation coefficient to assess the relationships among observable behavioral dimensions, this study proposes a framework for optimizing the content logic of the educational enterprise's learning environment.

2. Complex Network Theory in Strategic Planning for Educational Enterprises

2.1. Complex Network Theory

Complex networks are abstract representations of complex systems in the real world. A complex network is defined as a network that exhibits some or all of the following properties: self-organization, self-similarity, attractors, small-world characteristics, and scale-free properties. The origins of complex network research are inextricably linked to graph theory, an important branch of mathematics, which also serves as the theoretical foundation for this field. A specific network can be abstracted as a graph $G=(V,E)$, consisting of a set of vertices V and a set of edges E. Let the number of vertices be $N=|V|$ and the number of edges be $M=|E|$. Each edge in E corresponds to a pair of vertices in V. A summary and generalization of the network graph is shown in Figure 1. By studying the structure and properties of graphs, we can better understand the nature of complex systems as a whole; the most classic example of this is the "Seven Bridges Problem." Solving this problem not only provided a detailed explanation of the issue but also pioneered the fields of graph theory and geometric topology. With the passage of time and scientific progress, scholars have discovered that many network patterns are gradually emerging in real life, characterized by diverse network scales and increasingly complex network structures.

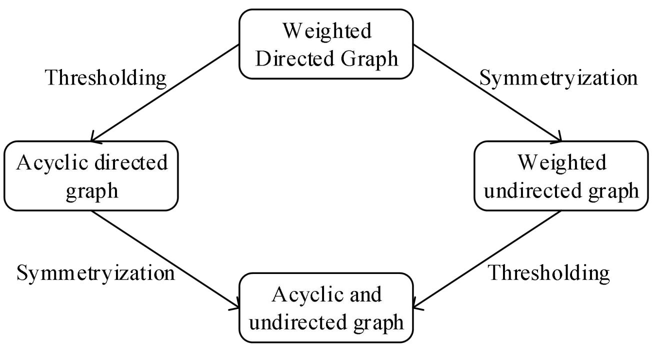

Figure 1. The relationships among the four basic types of network diagrams

2.2. Second Mock Exam Network

The scale-free network, often abbreviated as the BA scale-free network model, has made scale-free networks a major topic in network science research. Researchers argue that random graphs and small-world networks fail to account for two critical aspects of real-world networks: the special cases of preferential attachment and growth. It is well known that in real life, the overall scale of a network is constantly growing, whereas the number of nodes in small-world and random network models remains constant, resulting in a relatively fixed network structure. However, if new nodes are added, they are likely to connect to high-degree hub nodes, a phenomenon known as the Matthew effect. Based on this, the BA scale-free network model was designed:

$$\Pi i = \frac{k_i}{\Sigma_j k_j} \tag{1}$$

After the t step, the BA algorithm generates a network containing $N = t + m_0$ nodes and $mt + M_0$ edges, where M_0 is the number of edges $\left(0 < M_0 \leq \frac{1}{2} m_0 \left(m_0 -\right)\right)$ between the m_0 nodes of $t = 0$ at the initial time. Figure 2 illustrates the evolution of a BA network with the parameter $m_0 = M_0 = 4, m = 2.5$. Existing nodes are represented by solid circles, with the relative size of the circles corresponding to the relative size of the nodes' degrees. Each newly added node is represented by a hollow circle, which connects to two existing nodes in the network according to the priority connection mechanism.

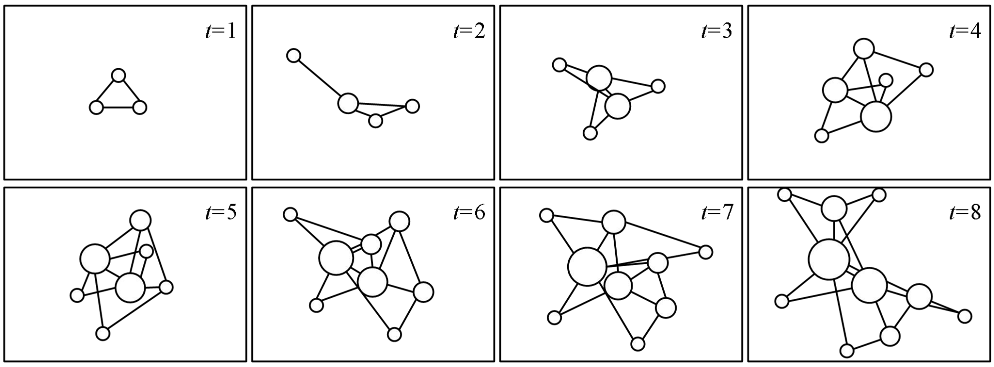

Figure 2. Evolution of the BA Model

In graph theory, a bipartite network is referred to as a bipartite graph; in network science research, it is known as a bipartite network, a subgraph, or a bipartite network. The existence of bipartite networks enables more effective extraction of meaningful insights from large datasets. As an important representation of complex networks, bipartite networks can more accurately reflect and explain the patterns of real-world networks, such as collaboration networks, student course selection networks, user recommendation networks, and online community networks. The common characteristics of bipartite networks are as follows: set X consists of a group of individuals, and set Y consists of events in which these individuals participate.

The specific mathematical representation can be expressed by the formula $Q = (G, B, C)$, where G and B represent any two connected nodes, and C represents the connection between any two nodes. Bimodal networks can be classified into incomplete bimodal networks and complete bimodal networks.

2.3. Methods for Calculating Network Characteristics

2.3.1. Average path length

In a complex network, an edge formed by two nodes connected directly or indirectly is called a path. The distance d_{ij} between nodes i and j is defined as the number of edges on the shortest path connecting the two nodes; it is also known as the geodesic distance or hop distance between the two nodes.

The average path length L of a network is defined as the average distance between any two nodes:

$$L = \frac{1}{\frac{1}{2} N(N-1)} \sum_{i \geq j} d_{ij} \tag{2}$$

Here, N represents the number of network nodes. Depending on the specific context, metrics such as harmonic mean and global efficiency are derived from the average path length; these metrics provide a better reflection of the flow of information between nodes in the network.

2.3.2. Clustering coefficient

In simple terms, the clustering coefficient can be understood as follows: two of your colleagues may not work in the same department, but they may still know each other. The likelihood of this mutual acquaintance reflects the closeness of the entire network of workplace relationships. In the language of network science, this degree of closeness is defined as the clustering coefficient. Therefore, in practice, assuming a network has i nodes, it has K_i neighboring nodes; however, these neighboring nodes (hereinafter referred to as "neighbors") are not necessarily all pairwise neighbors. Thus, the clustering coefficient C_i of a node i with degree K_i in the network is defined as:

$$C_i = \frac{2E_i}{k_i\left(k_i - 1\right)} \tag{3}$$

Here, E_i represents the number of actual edges among the K_i neighbors of node i, that is, the number of actual neighbor pairs among the K_i neighbors of node i. If node i has only one neighbor or no neighbors at all, then $E_i = 0$ indicates that there are no edges between any of the nodes, meaning the entire network consists of isolated nodes. If $C_i = 1$, then this proves that the network is a complete network, meaning that there is an edge connecting any two nodes in the network.

2.3.3. Degree distribution

Based on an understanding of the concept of degree in networks, degree distributions are primarily classified into Poisson distributions and power-law distributions. Here, p_k represents the proportion of network nodes (which can also be defined as the probability of randomly selecting a node with degree).

When a network follows a Poisson distribution, that is:

$$P(k) = \frac{\lambda^k e^{-\lambda}}{k!} \tag{4}$$

When the parameter $\lambda > 0$, the mean and variance of the Poisson distribution are both λ, and as λ increases, the shape of the distribution rapidly approaches that of a normal curve.

Both out-degree and in-degree distributions differ significantly from the normal distribution; instead, they follow a power-law distribution. Although degree distributions have long been a key focus in the study of network structure within the field of network science, as research has progressed, many experts and scholars have found that the degree distributions of some real-world networks cannot be adequately described by the Poisson distribution; rather, they are better represented by a power-law distribution:

$$P(k) \sim k^{-\gamma} \tag{5}$$

Here, $\gamma > 0$ represents the power exponent, which typically ranges between 1.5 and 2.5. When visualizing a power-law distribution, an analysis of the given data often reveals an approximate straight line in the coordinate system. This allows one to demonstrate that the data approximately follows a power-law distribution, and the corresponding power exponent can be derived from the slope of this line. However, in reality, there are virtually no actual networks that strictly follow a power-law distribution across the entire range of degree values. When people say that a specific network exhibits a power-law distribution, they generally mean that the distribution approximates a power-law form for large degree values; in this context, the distribution is said to follow a power-law at the tail.

3. Optimizing Educational Business Strategies Based on Complex Network Analysis

This study uses Z Education as its case study. Z Education is a comprehensive education and training company dedicated to integrating online and offline services. Data on student learning outcomes was collected through the company's official website, surveys, and interviews.

3.1. Average path length

After conducting a second-order analysis, a total of 13,655 education enterprise users were found to be interconnected, forming a relatively large network. The average path in the network of education enterprise user selection behavior is shown in Figure 3, with an average path length of 2.471. Betweenness centrality reflects control capacity, indicating the number of times a node lies on the shortest path between other nodes; a higher value indicates that the node is more central. In contrast, betweenness centrality reflects the ability to avoid control, representing the sum of the shortest path distances between a node and other members; a higher value indicates that the member is less central. The betweenness centrality and betweenness centrality in the online education user choice behavior network corroborate each other, providing clear evidence that the analysis conclusions are accurate. The core nodes in this network are clearly identified, and the degree of control is relatively clear. Excentricity reflects the maximum number of shortest paths a node can reach in the network; in the figure, the shortest paths of most nodes are concentrated at values of 1 and 7. Harmonic centrality, as a new algorithmic metric and a variant of betweenness centrality, is used for undirected graph analysis. Since the network structure after binarization is undirected, harmonic centrality is employed to characterize it; the data in the figure indicates that it generally aligns with the concentration scale observed in betweenness centrality.

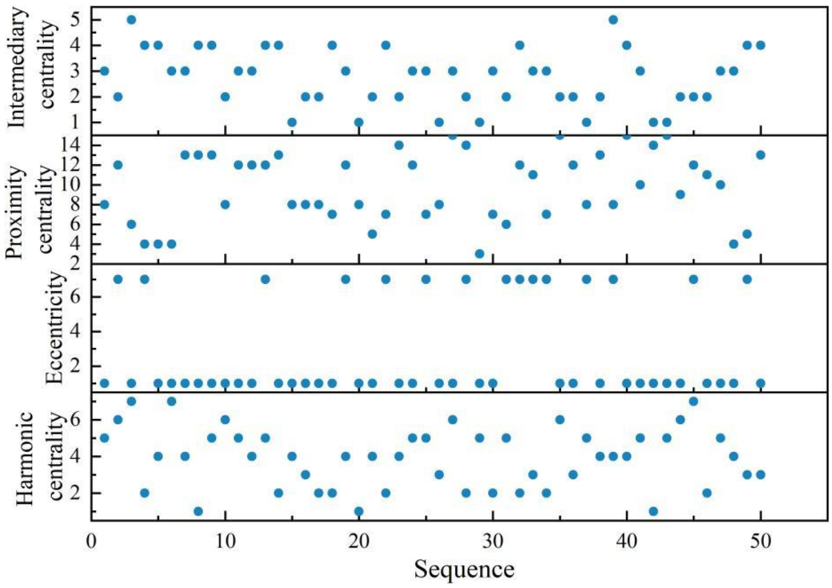

Figure 3. Average path of user selection behavior network

3.2. Average clustering coefficient

As shown in the network diagram, the distribution of courses selected by users of educational companies is relatively scattered. There are many factors contributing to this phenomenon, such as the degree of familiarity among users and the degree of correlation between courses. Although the distribution is scattered, careful observation reveals that some nodes still exhibit clustering characteristics. The average clustering coefficient of the user choice behavior network is shown in Figure 4. The analysis yields a network clustering coefficient of 0.211. Although this value is not particularly high, 0.211 is significantly greater than zero, proving that associations do indeed exist between nodes. This confirms that the overall network structure follows a complex network model. Given that the data accurately reflects the unique characteristics of educational enterprise users' course selection behavior, this value can be considered consistent with the concept of a network possessing a relatively high clustering coefficient. Following the two-model analysis, the network comprises 158 nodes and 422 edges. Although the network is large in scale, it exhibits a short average path length (2.471) and a high clustering coefficient, consistent with the characteristics of the small-world model.

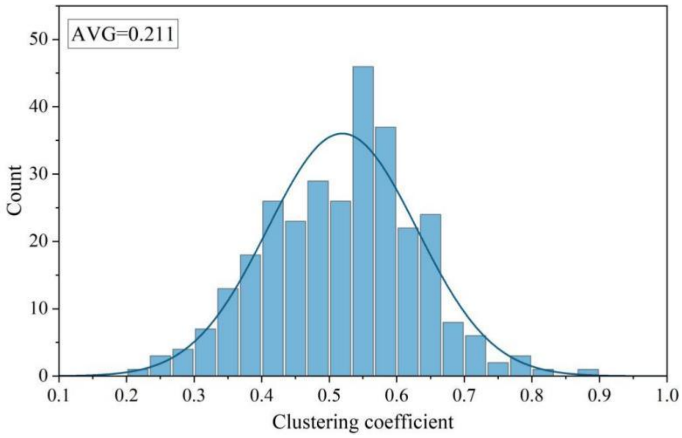

Figure 4. Average clustering coefficient of the user's choice behavior network

3.3 Scale-free properties

The scale-free property refers to a power-law distribution phenomenon in which, when the number of nodes (entities) in a social network reaches a certain threshold, a small number of nodes possess a large number of connections, while the vast majority of nodes have only a few connections. Although this paper employs a bimodal network construction method, analysis of the actual situation indicates that when users who have selected one course subsequently choose another identical course, this represents a two-way recognition: users express a need to learn, and the course meets that demand. Therefore, the network of user selection behavior is identified as an undirected network. The degree distribution of nodes in the user selection behavior network is shown in Figure 5. The user behavior network exhibits a power-law distribution, with a small number of users establishing extensive connections within the network, while the majority of users establish only a few connections. Among all 185 courses offered by the educational institution, 144 courses (77.8%) have a degree centrality of 6 or less, while 11 courses (5.9%) have a degree centrality of 15 or more. This indicates a clear non-uniform distribution of degree centrality in the user selection behavior network. Furthermore, the highest degree centrality recorded is 27; compared to findings in other studies, this value is relatively substantial and consistent with reality.

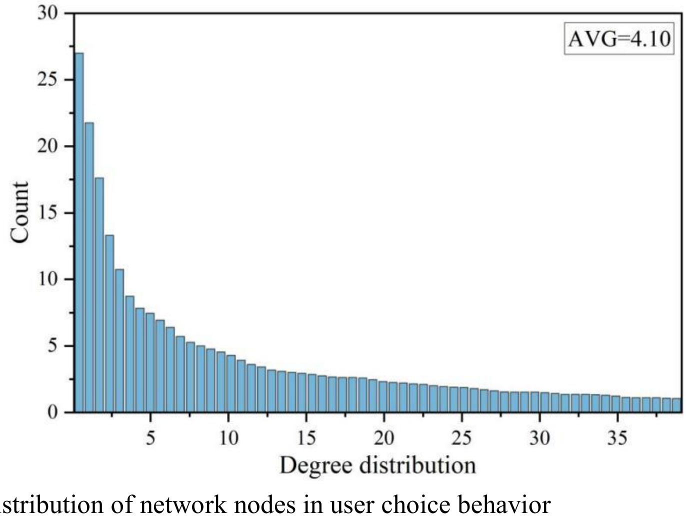

Figure 5. Degree distribution of network nodes in user choice behavior

Based on an analysis of Z Education and Training Company's overall teaching network using complex network theory, the company can implement a phased curriculum with small-class instruction and establish an effective communication mechanism with students' parents to achieve the goal of joint supervision by the school and parents. At the same time, the company should increase incentives for group enrollments and offer greater discounts for sharing course information via new media platforms such as QQ and WeChat. When selecting instructors, the company must spare no expense in hiring experienced teachers with a solid foundation in their subject matter and a humorous, engaging teaching style. This is also of paramount importance for expanding the market and attracting students.

4. Data Analysis Model for Learning Environments in the Education Sector

4.1. Learning Data Analysis Methods

Cluster analysis, often referred to simply as clustering, is a key component of data mining. It involves identifying meaningful patterns of data distribution within hidden, seemingly random data. Without any predefined grouping rules, the data is divided into distinct clusters based on its inherent characteristics, thereby achieving the effect of "like groups together."

This paper selects the K-means algorithm, whose core concept revolves around classification and distance. First, the n objects in the sample are divided into k distinct clusters using a specific method. Then, a corresponding algorithm is employed to determine a clustering solution that minimizes the sum of the squares of the distances from each object in a cluster to its cluster center. This achieves the goal of clustering, ensuring high similarity within the same cluster, while ensuring low similarity between different clusters. Similarity is calculated based on the average of all objects within the same cluster. E is the sum of the squared errors of all objects in the database; p is a point in space; in the algorithm, the $C_i, i = 1, 2, 3\ldots, k$ value is used to distinguish between clusters of n objects; m_i is the cluster center, i.e., the center point of the cluster. This calculation process is repeated iteratively until the average value is finally computed. The calculation formula is shown in (6):

$$E = \sum_{i=1}^{k} \sum_{p \in C_i} \left(p - m_i\right)^2 \tag{6}$$

To conduct a more in-depth analysis of learners' behavioral characteristics during online learning on an e-learning platform, this study selected the necessary data and performed cluster analysis on it. Clustering of learning behaviors involves grouping similar data results obtained by learners after studying on the platform into the same type of learning behavior. Cluster analysis was conducted based on five aspects: learners' completion rates for course videos, number of course visits, completion rates for course materials, assignment completion rates, and chapter quiz completion rates. By identifying certain characteristics of learning behavior through this analysis, we aim to address shortcomings in learners' behavior. This approach will help improve learning behavior on the online teaching platform, provide more persuasive recommendations and suggestions for advancing the platform's sustainable development, refining teaching management, enhancing the learning process, continuously updating learning resources, and improving the surrounding learning environment.

Correlation analysis is one of the commonly used methods in data analysis. It allows us to identify relationships between data points and make predictions based on correlation coefficients. The Pearson correlation coefficient is used to measure the linear relationship between variables of equal rank. In the correlation analysis of the dimensions of overt behavior, the method employed is the Pearson correlation coefficient, also known as the matrix correlation coefficient. It is a linear correlation measure used to assess the relationship between two variables, and its calculation model is shown in Equation (7):

$$r = \frac{\sum (x - \overline{x})(y - \overline{Y})}{n \times \sigma_x \times \sigma_y} \tag{7}$$

In the formula, σ_x, σ_y represents the standard deviation of the two variables, n is the sample size, and r is defined as the sum of the products of the two standard scores divided by the sample size. r takes values between -1 and +1; a positive value for r indicates a positive correlation between the two variables, a negative r value indicates a positive correlation between the two. When the correlation coefficient is $r = 0$, it indicates that there is no linear correlation between the variables; when the correlation coefficient is $0 \le |r| \le 0.3$, it indicates a weak correlation between the variables; when the correlation coefficient is $0.3 < |r| \le 0.5$, it indicates a low correlation between the variables; when it is $0.5 < |r| \le 0.8$, it indicates a significant correlation between the variables; when it is $0.8 < |r| < 1$, it indicates a high correlation between the variables; and when it is $|r| = 1$, it indicates a perfect linear correlation between the variables.

After analyzing learners' behavioral data, this study investigates the relationships among their various learning behaviors. This paper employs Spearman's correlation coefficient to analyze the correlations among different learning behaviors. This method measures linear relationships between variables, and the computational model does not require the data to follow a normal distribution. The computational model is shown in Equation (8):

$$r = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n^3 - n} \tag{8}$$

Spearman's method requires paired data from ordinal variables or ordinal data derived from multiple continuous variables. Regardless of the overall distribution trend between the two variables or the sample size, Spearman's rank correlation coefficient can be used to analyze the relationship between them. The results of a Spearman correlation analysis depend on the absolute value of r, which ranges from -1 to +1. r indicates the strength of the correlation between two variables, $r > 0$ indicates a positive correlation, $r < 0$ indicates a negative correlation, and $r = 0$ indicates no correlation.

4.2. Innovation and Optimization of the Learning Environment

In the optimization of learning environments established by educational enterprises, the internal interactions among smart administrators, smart teachers, and smart learners exert subtle yet significant influences on one another, subsequently driving the utilization of underlying infrastructure services. The internal logical relationships within an educational enterprise's smart learning environment are illustrated in Figure 6. Specifically, this is achieved through the use of smart terminals, which support user activities. These terminals connect to the facility via Wi-Fi, radio frequency technology, or geolocation methods. The facility identifies the various terminal devices present and provides corresponding interfaces, further integrating facility information to connect to the smart teaching platform; Within the platform, the interaction among the three core modules—the User Center, Resource Center, and Data Center—ultimately influences human resource development. By leveraging various technologies, the platform provides services such as personalized learning diagnostics and context-specific learning materials, fostering new insights into human resource development and ultimately forming a circular feedback loop; Human resource development also influences institutional development. The mindset of individuals affects their choices regarding teaching methods, learning approaches, and management practices. Of course, institutional development plays a guiding role in human resource development and ensures the foundation of the system. Furthermore, the foundational infrastructure inevitably influences institutional development, thereby affecting learning methods, teaching approaches, and management practices.

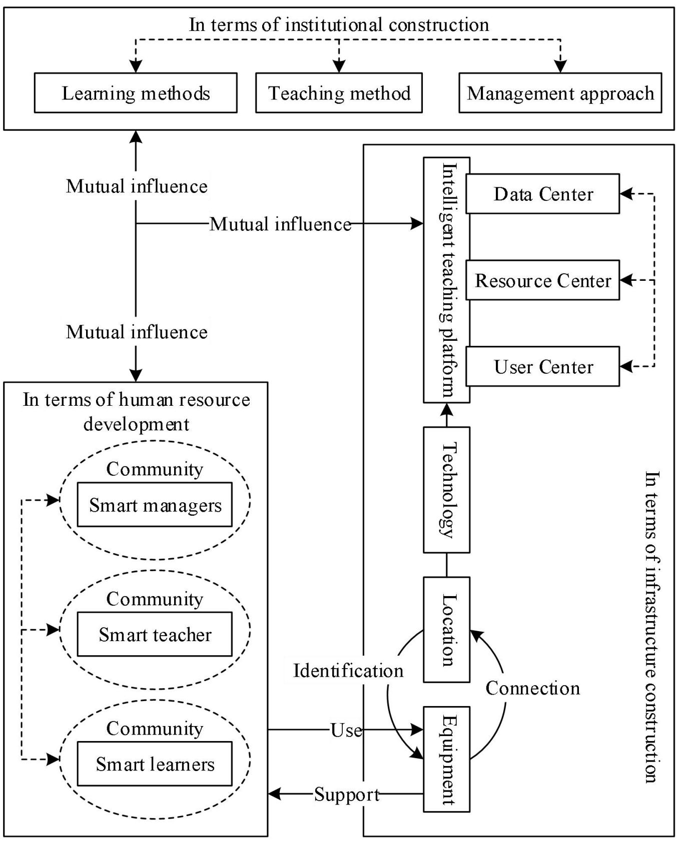

Figure 6. The internal logical relationship of the intelligent learning environment

5. Optimizing Computing Resources for Educational Institutions

5.1. List of Key Concepts and Attributes

Based on the educational enterprise network diagram derived earlier, and in conjunction with the quantitative calculation method proposed in Chapter 4 of this paper, we can obtain the attribute values for each knowledge point (difficulty level D_i, learner mastery level A_i, and importance level I_i) as well as the attribute values for the relationships between knowledge points (learning cost S_{ij} and learning experience evaluation H_{ij}). Table 1 presents the calculated values of the attributes associated with each knowledge point, normalized to the interval [0,1], where the difficulty ranges from [0.20, 0.95], the learner's mastery ranges from [0.15, 0.91], and the importance ranges from [0.21, 0.89].

Table 1. The calculation results of the attribute values related to the knowledge points

K_i	D_i	A_i	I_i
K_1	0.78	0.61	0.43
K_2	0.39	0.91	0.87
K_3	0.66	0.25	0.73
K_4	0.25	0.78	0.42
K_5	0.20	0.27	0.62
K_6	0.80	0.17	0.68
K_7	0.80	0.59	0.5
K_8	0.75	0.33	0.44
K_9	0.55	0.67	0.84
K_{10}	0.34	0.62	0.80
K_{11}	0.93	0.83	0.89
K_{12}	0.67	0.17	0.85
K_{13}	0.93	0.63	0.79
K_{14}	0.73	0.27	0.23
K_{15}	0.37	0.61	0.88
K_{16}	0.53	0.15	0.45
K_{17}	0.33	0.39	0.21
K_{18}	0.95	0.85	0.35
K_{19}	0.48	0.53	0.62
K_{20}	0.50	0.79	0.62

Table 2 presents the calculated results for the correlation attribute values between selected (the first 8) knowledge points. The learning experience evaluation scores were normalized to positive integers in the range [1, 10], with higher values indicating greater satisfaction with the learning experience. Among the first 8 knowledge points, the pair with the highest correlation attribute value is (K_4, K_5), with a transfer attribute of (10, 10).

Table 2. The attribute values of the transfer relationships between knowledge points

(S_{ij},H_{ij})	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8
K_1	(5,1)	(1,6)	(0,0)	(9,7)	(9,7)	(3,3)	(2,9)	(7,3)
K_2	(6,5)	(9,0)	(7,8)	(5,7)	(2,4)	(1,6)	(7,5)	(4,3)
K_3	(2,1)	(1,2)	(7,8)	(1,3)	(8,8)	(4,4)	(9,4)	(8,4)
K_4	(1,1)	(5,2)	(8,1)	(5,1)	(10,10)	(3,3)	(1,6)	(3,9)
K_5	(6,6)	(9,7)	(8,7)	(4,5)	(6,9)	(7,5)	(7,2)	(1,5)
K_6	(3,5)	(9,4)	(8,7)	(1,8)	(7,5)	(9,2)	(4,4)	(9,1)
K_7	(6,7)	(3,9)	(1,7)	(3,4)	(2,6)	(5,1)	(0,7)	(7,1)
K_8	(7,3)	(8,9)	(6,6)	(3,5)	(5,1)	(5,4)	(7,8)	(6,9)

5.2. Results of Learning Environment Optimization

Based on the knowledge point attributes described in the preceding section, and in conjunction with the computational optimization algorithm presented in this paper, we can calculate the degree of difference between each knowledge point within the knowledge point subgraph. According to the optimization model in this paper, we used the computational method to obtain the average degree of difference from 15 experiments, excluding the degree of difference between a knowledge point and itself. Table 3 shows the average degree of difference for a selection of knowledge points. We can obtain the difference values between any two knowledge points; the average difference, excluding self-pairs, is 0.958. The final experimental result of this model is to plan a reasonable learning sequence for learners, that is, to generate fine-grained learning paths with knowledge points as nodes. Therefore, based on the calculated difference values between knowledge points and in combination with the learning environment path optimization process mentioned in this paper, we can derive the optimized learning environment path.

Table 3. Average degree of knowledge differences

	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8
K_1	0.000	1.105	0.481	0.393	0.929	1.295	1.269	0.779
K_2	1.190	0.000	0.417	1.061	0.360	0.632	0.941	0.649
K_3	1.224	0.585	0.000	0.712	0.958	1.200	0.669	1.704
K_4	1.436	1.609	1.148	0.000	1.775	0.854	0.873	0.745
K_5	0.345	1.300	1.583	1.214	0.000	0.837	0.641	1.609
K_6	1.764	1.526	0.149	1.515	1.394	0.000	1.633	0.876
K_7	1.244	0.174	0.373	0.846	0.399	1.269	0.000	0.039
K_8	0.768	1.525	0.256	0.968	0.008	1.502	0.948	0.000

6. Conclusion

This paper employs complex network theory and learning environment data analysis methods to optimize the strategic planning network and learning environment pathways of Z Education. By focusing on two key aspects—the instructional network of the company's students and the link characteristics of knowledge points within the learning environment—the study analyzes the company's instructional environment data.

The average path length of the behavioral network for corporate users in the education sector is 2.471. The network has clearly defined core nodes with high control strength, and the eccentricity values are concentrated around 1 and 7. Additionally, the network has a clustering coefficient of 0.211, with 158 nodes and 422 edges, exhibiting characteristics of a small-world network. An analysis of the overall educational network can help guide strategic planning.

Analysis of the learning environment path data revealed that the ranges for difficulty, learner mastery, and importance were [0.20, 0.95], [0.15, 0.91], and [0.21, 0.89], respectively. The average variance of knowledge points was 0.958, resulting in an optimized learning environment path.

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