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Analysis of professional competency awareness based on visible network graphs

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Introduction: With the advancement of society and technology, the importance of professional competency has been increasingly emphasized. This study aims to provide an in-depth analysis of the Baidu search index for "professional competency" from July 3, 2017, to October 6, 2023, across 34 provincial-level administrative regions in China.

Methods: The study begins with a literature review to establish a theoretical framework. Subsequently, it delves into the fundamental concepts of complex networks, their parameters, and the principles of visible network graph algorithms. The application of system clustering and community detection algorithms is explored within this framework.

Results: The empirical analysis starts with a provincial-level examination, involving the construction of visible network graphs, the exploration of scale-free networks, and discussions on regional system clustering. Following this, a nationwide analysis is conducted, focusing on the construction of visible network graphs to visualize the awareness of professional competency and studying community structures.

Discussion: The findings provide insights into the awareness of professional competency across different regions. These insights are valuable for informing policy formulation and corporate decision-making, contributing to a deeper understanding of professional competency awareness and its implications.

KEYWORDS

visible network graphs, professional competency, awareness, Baidu search index, complex networks

1 Introduction

With the advancement of globalization and rapid economic development, technology plays an increasingly crucial role in various fields, leading to profound changes in the job market and work environments. In this context, people's expectations and focus on their own career development and personal growth have significantly increased. They are now more concerned about how to enhance their professional skills to adapt to this fast-changing world.

In this trend, "professional competency" has emerged as a core concept, seen as a key indicator for measuring an individual's professional capabilities and overall qualities. Professional competency encompasses not only an individual's skills or knowledge but also a comprehensive reflection of various aspects, including attitude, values, communication abilities, and teamwork spirit. This competency directly impacts an individual's performance in the workplace and determines whether they can successfully plan and develop their careers.

More importantly, the improvement of professional competency is closely linked to national human resource development strategies, corporate talent selection criteria, and training mechanisms, as well as the overall harmony and stability of society. When an individual's professional competency improves, they can not only create more value for the company but also contribute to the progress and prosperity of society.

Therefore, research on the awareness of "professional competency" is of significant theoretical and practical importance. However, traditional research methods often rely on qualitative descriptions and analysis, lacking in-depth exploration and analysis of extensive data. To address this, this paper employs a method based on visible network graphs to conduct an in-depth study of the awareness of "professional competency" in the Baidu Consultation search index. This approach provides a more intuitive and accurate way to reveal changes in the awareness of professional competency in different regions and time periods, offering strong data support for relevant policy-making and corporate decision-making.

The research methodology in this paper combines complex network theory and big data analysis techniques, enabling effective processing and analysis of large search data and revealing patterns and trends.

The visibility graph network method, compared to existing traditional analytical methods, demonstrates unique advantages and significant differences in analyzing attention towards professional competencies. This method, by converting time-series data into network structures, offers researchers a novel perspective, allowing them to intuitively reveal the complex relationships and dynamic changes among the data, which are often difficult to achieve with traditional linear analysis methods [1–3]. The visibility graph network can uncover the scale-free and fractal properties of the data, aiding in a deeper understanding of the nonlinear characteristics of the temporal and spatial distribution of attention towards professional competencies, aspects frequently overlooked by traditional methods. Additionally, by leveraging complex network analysis tools such as systematic clustering and community partitioning, key periods of attention and regional disparities can be identified, providing more precise and personalized guidance for professional competency research and policy formulation.

2 Literature review

In recent years, the visibility graph network method has been widely applied in various fields of research. Sen Jiang employed visibility network methods to analyze heart rate variability signals in his study [4], providing a novel perspective for the processing of time series data. Similarly, Lian Zhou utilized methods based on visibility and evidence theory to study prediction algorithms for time series, achieving certain effectiveness in practical applications [5]. Both studies indicate that visibility graph network methods have high practical value in the analysis of time series data. Zhihui Zhou et al., using "vocational education" as a keyword, selected Baidu search index data from 2013 to 2022 for 29 provinces in China. They transformed time series data into complex networks using the visibility graph method and explored the network characteristics and regional differences in the attention to vocational education through methods such as network parameters, degree distribution, and hierarchical clustering [6]. Regarding the application of systematic clustering methods, Xinyu Yu selected 645 literature samples on research on the data literacy of Chinese university students from the China National Knowledge Infrastructure (CNKI) database for the years 2003–2022. The COOC 9.94 software was used to analyze the publication years, journals, research institutions, core authors, and keywords of the sample literature, investigating the current status and research hotspots of university students' data literacy [7].

Closely related to the theme of this study is the research conducted by Mengyue Zhang et al., where visibility graph networks were used to analyze the attention to Chinese patent applications. This not only demonstrated the application of complex network analysis in the field of intellectual property but also highlighted the role of community partitioning in determining key areas and hot issues. They used systematic clustering and community partitioning to identify key factors influencing the visibility of papers on social media [8], providing an intuitive example that demonstrates the potential application of visibility graph network methods in attention analysis. Additionally, Hailin Li and Liping Zhang conducted a review on clustering in time series data mining [9], presenting various methods and approaches for processing time series data.

In the study of vocational literacy, Siyin Gao and Nana Jia explored strategies and paths for cultivating vocational core literacy in higher vocational students from the perspectives of production-education integration and higher vocational colleges [10, 11]. This provides multiple perspectives and methods for the cultivation of vocational literacy. Gang Li et al. Conducted predictive research on the social media visibility of academic papers, offering a new research direction on how to increase social media attention in vocational literacy studies. In Li Gang's study on the prediction of social media visibility of academic papers, complex network parameters such as node influence and network modularity might be used to understand and predict the dissemination patterns of papers on social media [12].

Furthermore, Rui Li et al. explored the hotspots and trends in the research of early special education in China through knowledge graph analysis [13], representing an application example of knowledge graphs in educational research. Meanwhile, Jianping Zheng and Yongshi Hu studied the temporal simultaneous lag effects based on a time series network similarity model [14], demonstrating the application of time series networks in other fields.

In summary, existing research has provided rich theoretical foundations and empirical cases for this study. Methods based on visibility graph networks show tremendous potential in the analysis of time series data, attention analysis, and vocational literacy research. This study will build upon these research achievements to further explore the practical progress and value of "Occupational Literacy Attention Analysis Based on Visibility Graph Networks."

The visibility graph network method effectively transforms time-series data into network structures, uncovering the temporal characteristics of attention towards professional competencies and providing a novel perspective for data comprehension. By

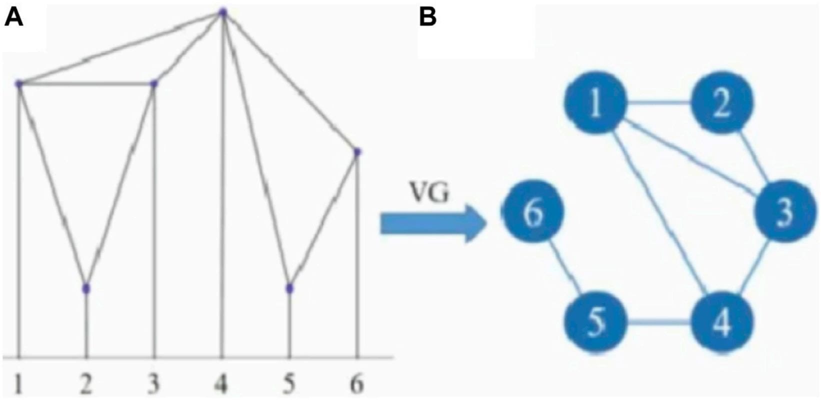

FIGURE 1
Visibility graph algorithm.

constructing complex networks, this study reveals the variations in attention towards professional competencies across different regions and time periods, thus offering robust data support for relevant policy-making and corporate decision-making. Additionally, leveraging the visibility graph network, the research discovers that search data for "professional competencies" in various provinces exhibit scale-free and fractal characteristics, providing theoretical support for further investigation. Through systematic clustering, significant differences in attention towards "professional competencies" among different provinces are identified.

3 Concepts

3.1 Basic concepts of complex networks

Complex networks constitute a multidisciplinary field focused on exploring the network structures within various complex systems, their internal dynamic behaviors, and the interactions and connections among their components. Complex systems are pervasive in both our daily lives and the natural world, spanning various domains such as technology, society, and biology [15]. Examples of complex networks include the Internet, social networks, ecosystems, and neural networks. These networks share the common characteristic of being composed of numerous nodes and edges, where the interactions and connections between these nodes and edges form the fundamental structure of the network. These structures often follow specific patterns and rules, rather than being random [16–18]. Research on complex networks not only examines the topology of these networks but also delves into dynamic processes within the network, such as information propagation, disease spreading, and collective behavior [19–21].

The primary goal of complex network research is to unveil statistical properties of these networks, such as degree distributions, clustering coefficients, and average path lengths, and to explore the universal principles and rules underlying these properties [22, 23]. By studying these statistical properties, one can gain a better understanding of the mechanisms, stability, and resilience of networks, as well as various dynamic processes within them. Additionally, research on complex networks provides a range of tools and methods for analyzing, predicting, and controlling the behavior of various complex systems, thereby finding practical applications across multiple domains, including technology, economics, and society [24].

3.2 Parameters of complex networks

3.2.1 Average path length

The average path length refers to the average length of the shortest paths between all pairs of nodes in the network [25]. It reflects the overall connectivity of the network, i.e., the average number of steps required for information or any other entity to propagate through the network. Mathematically, given an adjacency matrix A for a network, the average path length L can be defined as:

$$L = \frac{1}{N(N-1)_{i\neq j}} \sum_{i\neq j} d(i,j) \tag{1}$$

Where N is the number of nodes in the network, and d (i, j) is the length of the shortest path between nodes i and j [5].

3.2.2 Clustering coefficient

The clustering coefficient describes the density of connections among a node's neighbors in the network [26]. For a given node, its clustering coefficient is the ratio of actual edges between its neighbors to the potential edges that could exist among them. For node i, its clustering coefficient Ci is defined as:

$$C_i = \frac{2e_i}{k_i(k_i-1)} \tag{2}$$

Where ei is the number of edges among the neighbors of node i, and ki is the degree of node i [5].

3.2.3 Degree distribution

Degree distribution describes the proportion of nodes in the network that have a specific degree k [27]. It reflects the network's connectivity pattern and structure. In many real networks, the

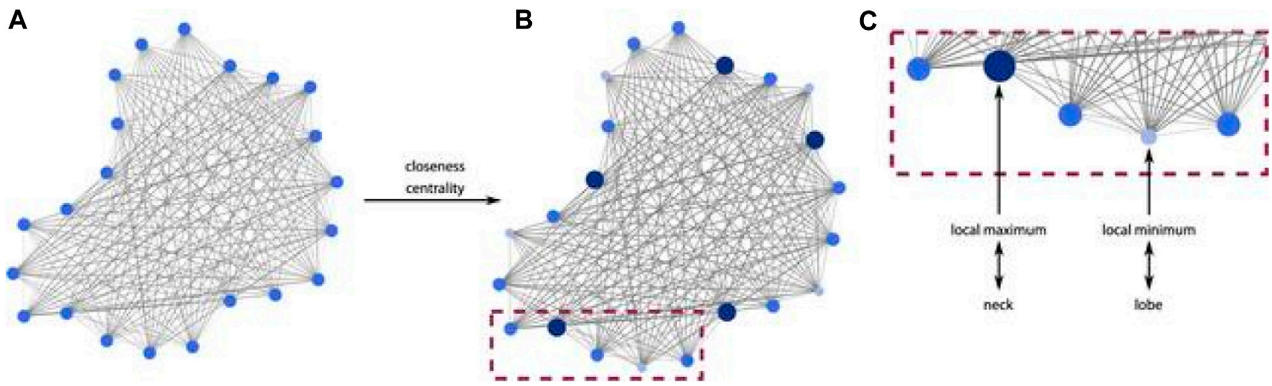

FIGURE 2
Network feature extraction of visibility graph.

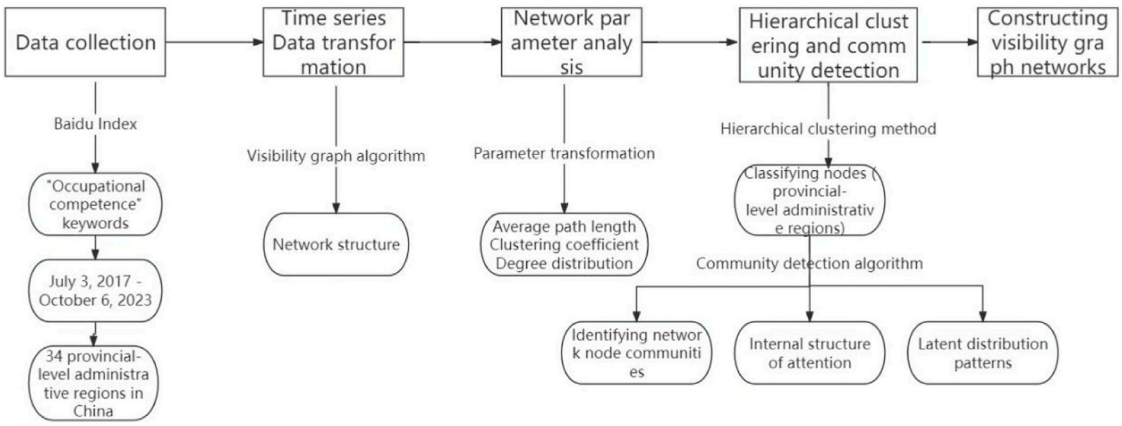

FIGURE 3
Visibility network diagram research framework.

degree distribution often follows a power-law distribution, where the majority of nodes have low degrees, and a few nodes have very high degrees. Mathematically, a power-law degree distribution can be expressed as:

$$P(k) \sim k^{-\alpha} \tag{3}$$

Where α is a constant, typically ranging between 2 and 3 [5].

3.3 Principles of visible network graph algorithms

The visible network graph algorithm is a method that transforms time series data into a network structure. The fundamental idea behind this algorithm is to treat each data point in the time series as a node and determine whether there is an edge between nodes based on certain "visibility" criteria [28]. Specifically, if the line between two data points is not obstructed by other data points, there is an edge between those two data points. This approach allows the transformation of nonlinear time series data into a graph structure, enabling the use of graph theory methods for analysis [29, 30].

In this study, the visible network graph algorithm was employed to analyze the awareness of "professional competency." Specifically, data for the Baidu Consultation search index related to "professional competency" was collected from 3 July 2017, to 6 October 2023, and denoted as a time series S(t), where t represents the time point.

In Figure 1, using the visibility graph algorithm, the time series S(t) has been transformed into a network structure G (V, E), where V is the set of nodes representing the search index at various time points, and E is the set of edges determined based on the visibility criteria. Specifically, if the line between two time points ti and tj, with search indices S (ti) and S (tj), is not obstructed by the search indices of other time points, then there exists an edge eij connecting ti and tj in the network G (V, E) [31–33].

In Figure 2, by constructing this network G (V, E), a complex network structure describing the changes in the awareness of "professional competency" over time has been obtained. This network not only reveals the time series characteristics of "professional competency" awareness but also provides a new perspective for analyzing the underlying dynamic mechanisms. For example, by analyzing the network's topological structure, such as degree distribution P(k), clustering coefficient C, and

TABLE 1 Visibility network parameters.

Province	Average degree	Diameter	Average path length	Density	Average clustering coefficient
Anhui	30.494	5	2.150	0.030	0.834
Beijing	15.153	5	2.453	0.015	0.825
Fujian	38.248	4	2.810	0.038	0.830
Gansu	31.393	5	2.135	0.031	0.834
Guangdong	36.419	4	2.085	0.036	0.831
Guangxi	28.345	5	2.165	0.028	0.831
Guizhou	32.728	5	2.127	0.033	0.833
Hainan	31.782	5	2.129	0.032	0.833
Hebei	21.036	5	2.289	0.021	0.823
Henan	37.161	4	2.083	0.036	0.831
Heilongjiang	38.395	4	2.081	0.038	0.830
Hubei	38.058	4	2.081	0.037	0.830
Hunan	29.728	5	2.153	0.030	0.834
Jilin	23.692	5	2.256	0.024	0.826
Jiangsu	37.444	4	2.082	0.037	0.831
Jiangxi	30.137	5	2.152	0.030	0.835
Liaoning	22.843	5	2.261	0.023	0.826
Inner Mongolia	30.815	5	2.145	0.031	0.834
Ningxia	33.187	5	2.124	0.033	0.834
Qinghai	33.681	5	2.123	0.033	0.834
Shandong	14.683	5	2.609	0.015	0.820
Shanxi	29.032	5	2.158	0.029	0.832
Shaanxi	15.677	6	2.372	0.016	0.821
Shanghai	36.315	4	2.085	0.036	0.831
Sichuan	37.226	4	2.082	0.036	0.831
Tianjin	37.050	4	2.084	0.036	0.831
Tibet	34.925	5	2.099	0.035	0.833
Xinjiang	25.615	5	2.181	0.027	0.832
Yunnan	25.615	5	2.200	0.025	0.830
Zhejiang	38.081	4	2.081	0.038	0.830
Chongqing	37.343	4	2.082	0.037	0.831

From the perspective of the average degree, Fujian, Heilongjiang, and Zhejiang have relatively high average degrees, reaching around 38. This indicates that in these provinces, there is a high frequency of searches for "professional competency." On the other hand, Shandong and Shaanxi have relatively low average degrees, at 14.683 and 15.677, respectively, suggesting lower levels of awareness regarding "professional competency" in these regions.

average path length L, one can identify key periods of awareness and potential driving factors [34].

3.4 System clustering

System clustering is a method that groups nodes within a network based on their topological structure and attributes. In this research, considering the regional characteristics of "professional competency" awareness, a system clustering method was used to classify various provincial-level administrative regions. Specifically, given a network G (V, E), where V represents the node set, indicating various provincial-level administrative regions, and E represents the edge set, indicating the similarity in awareness between regions, the research objective is to find a node partition P = {C1, C2, C3, . . . , Ck}, where each Ci is a node subset representing a cluster [35].

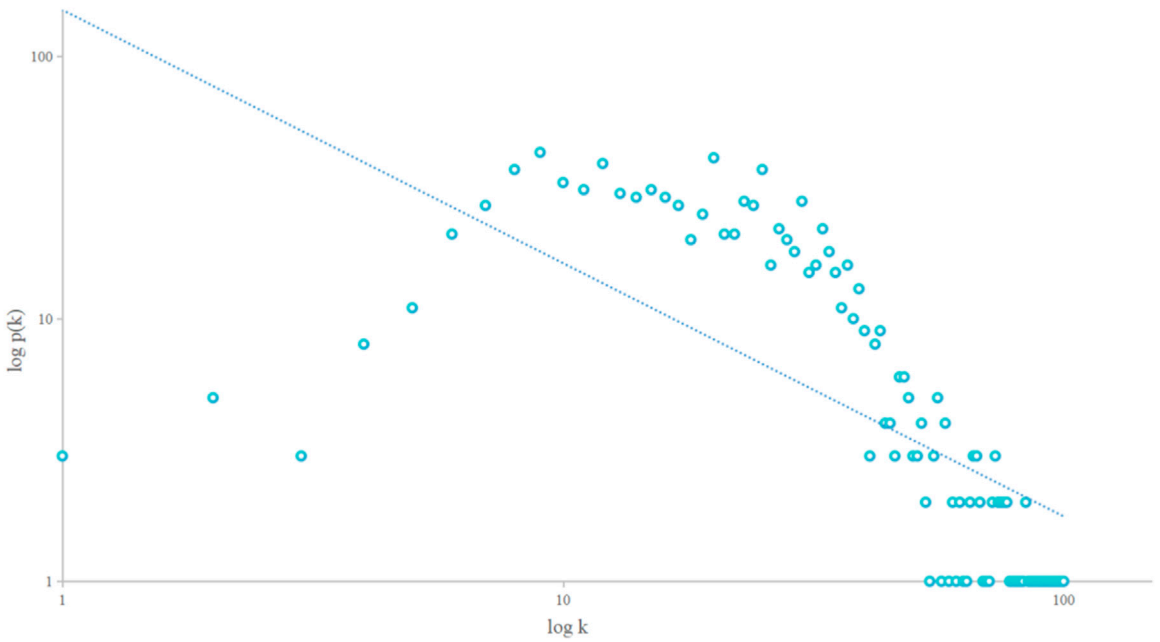

FIGURE 4
Power distribution of visibility network in Anhui province.

TABLE 2 Power law distribution and goodness of fit of visibility networks.

Province	Y	R	Province	Y	R
Anhui	0.965	0.4477	Liaoning	1.202	0.5596
Beijing	0.837	0.3662	Inner Mongolia	0.974	0.4495
Fujian	0.926	0.4563	Ningxia	0.936	0.4228
Gansu	0.987	0.4544	Qinghai	0.888	0.3920
Guangdong	0.808	0.3468	Shandong	1.415	0.6454
Guangxi	1.058	0.4901	Shanxi	1.009	0.4656
Guizhou	0.931	0.4275	Shaanxi	1.295	0.6044
Hainan	0.974	0.4479	Shanghai	0.830	0.3617
Hebei	1.251	0.5663	Sichuan	0.798	0.3484
Henan	0.794	0.3442	Tianjin	0.830	0.3638
Heilongjiang	0.927	0.4589	Tibet	0.864	0.3796
Hubei	0.907	0.4410	Xinjiang	1.104	0.5148
Hunan	1.022	0.4687	Yunnan	1.104	0.5148
Jilin	1.175	0.5500	Zhejiang	0.917	0.4465
Jiangsu	0.908	0.4392	Chongqing	0.829	0.3663
Jiangxi	0.996	0.4544			

To achieve this goal, a clustering algorithm based on modularity optimization was employed. Modularity Q is a metric that measures the quality of network clustering and is defined as:

$$Q = \sum_{i=1}^{k}\left[\frac{|E(C_i, C_i)|}{|E|} - \left(\frac{|E(C_i, V)|}{|E|}\right)^2\right] \quad (4)$$

Where |E (Ci, Ci)| is the number of edges within the subset Ci, and |E (Ci, V)| is the number of edges between the subset Ci and the entire network V [9].

3.5 Community detection algorithm

Community detection is a core problem in the study of complex networks, aiming to identify tightly connected groups of nodes within a network. In this study, a community detection algorithm was employed to further refine the structural characteristics of "professional competency" awareness. Specifically, given the aforementioned network G (V, E), the goal was to find a community partition S = {D1, D2, . . . , Dm}, where each Di is a node subset representing a community [9].

To achieve this goal, the Louvain algorithm was used, which is an efficient community detection method based on modularity optimization. The algorithm gradually improves the modularity Q through iterative processes of local optimization and community merging, ultimately obtaining the final community partition.

4 Data

This paper selected Baidu Consultation search index as the data source, covering search data related to "professional competency"

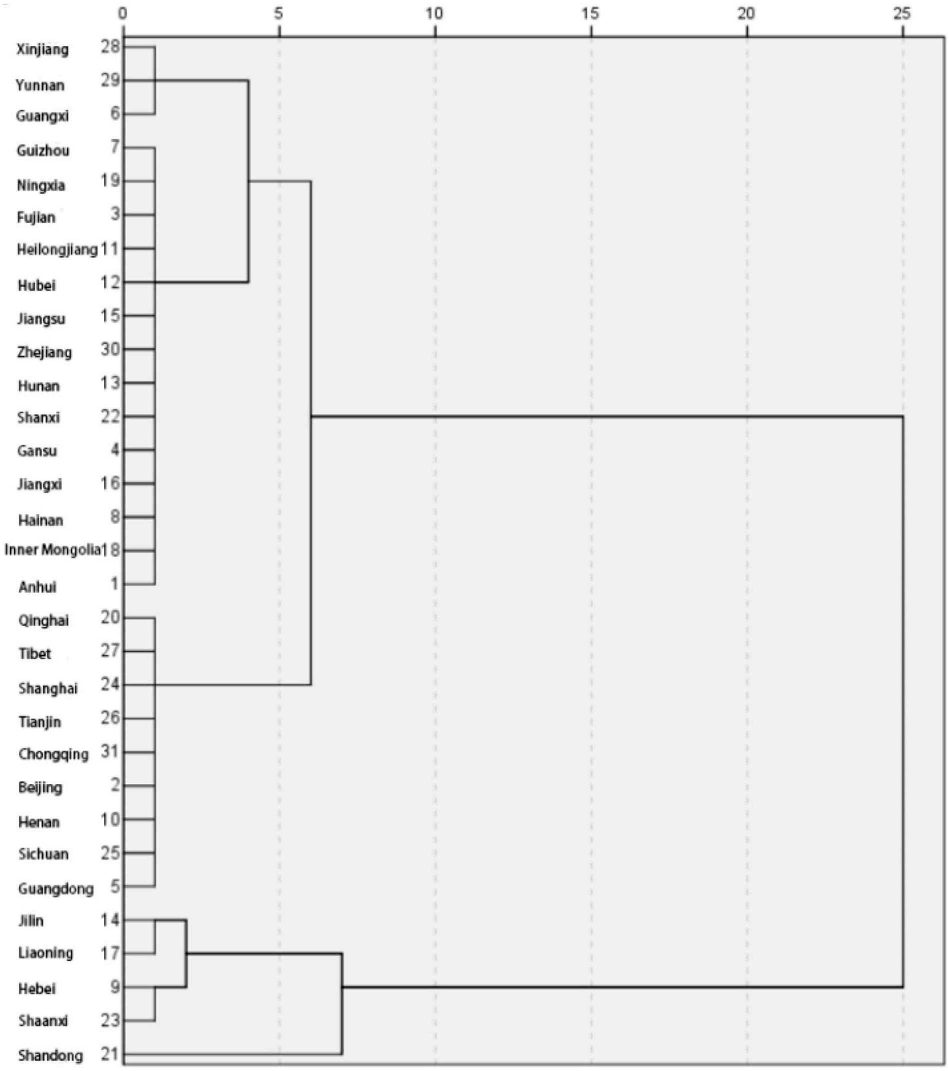

FIGURE 5
System clustering results.

from 3 July 2017, to 6 October 2023. The data was further disaggregated for all 34 provincial-level administrative regions in China (excluding data for Hong Kong, Macau, and Taiwan, which were all zero).

Choosing Baidu Consultation search index as the data source is grounded in several reasons. Firstly, as the largest search engine in China, Baidu's search data can effectively mirror the interests and concerns of a vast number of internet users, rendering it highly representative [36, 37]. Secondly, the search index transcends being a mere numerical value; it encapsulates a trove of social, economic, and cultural information [38, 39], providing both macro and micro perspectives on the awareness of "professional competency." Additionally, delving into data from various provincial-level administrative regions facilitates insights into the divergences and nuances of "professional competency" awareness across different regions and cultural backgrounds.

This paper initially employed the visibility graph algorithm to convert time series data into a complex network, illustrating the fluctuations in awareness of "professional competency" over time. Following this, through the application of system clustering and community detection algorithms, the network underwent a comprehensive structural analysis to pinpoint key nodes, tightly connected groups of nodes, and potential community structures. The specific research framework for visibility network analysis can be seen in Figure 3.

5 Empirical analysis of provincial data

5.1 Construction of visibility graph networks for Chinese provinces

With the progression of the economy and the advancements in information technology, there has been a steady rise in people's awareness of professional competency. To comprehensively comprehend this trend, this section delves into the analysis of search data for "professional competency" across 31 provincial-

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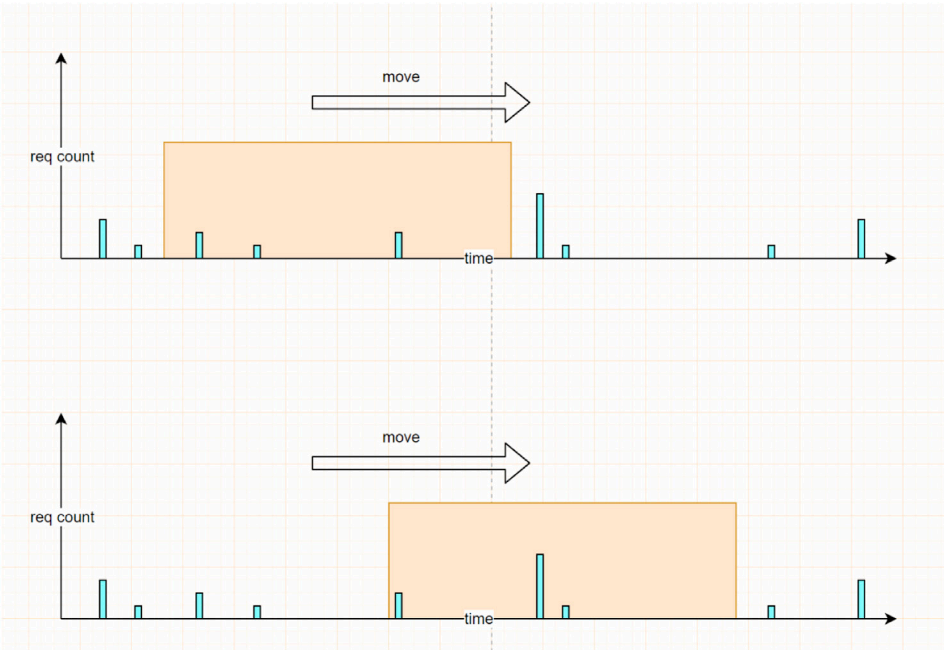

FIGURE 6
Time window moving schematic.

level administrative regions in China, utilizing the Baidu Consultation search index. The utilization of the visibility graph algorithm facilitates the transformation of time series data into a complex network, offering a detailed portrayal of the shifts in awareness of “professional competency” over time. This transformative approach enables observations and analyses at both macro and micro levels of the data.

Table 1 outlines the visibility graph network parameters for each province, encompassing average degree, diameter, average path length, density, and average clustering coefficient. These parameters collectively furnish a holistic perspective, aiding in the understanding of the level of awareness of “professional competency” in each province.

Next, the diameter parameter reveals that most provinces have a diameter of 4 or 5, indicating relatively high levels of association between any two time points in these provinces. The average path length for most provinces falls between 2.0 and 2.6, indicating a relatively fast rate of information propagation within the network.

The density parameter shows that most provinces have densities ranging from 0.02 to 0.04, implying highly interconnected nodes within the network and good continuity and stability in information propagation.

Finally, looking at the average clustering coefficient, it’s evident that the average clustering coefficients for all provinces are above 0.8. This indicates a high level of closeness in the connections between nodes and their neighbors in the network, reflecting the widespread awareness to the topic of “professional competency” in these provinces.

In summary, Table 1 reflects the network structural characteristics of awareness regarding “professional competency” in various provinces. These parameters provide a deeper understanding of the characteristics of awareness in each province, offering robust data support for further research.

5.2 Scale-free networks: fractal time series

A scale-free network is one where the majority of nodes have very few connections, while a small number of nodes have a large number of connections. The degree distribution in such networks follows a power-law distribution, meaning the relationship between the node degree and its frequency can be described using a power-law. Fractal time series, on the other hand, are time series with self-similarity, meaning they exhibit similar statistical characteristics at different time scales [40, 41].

In this section, we will explore whether the “professional competency” search data for each province exhibits scale-free and fractal characteristics. To do this, we first construct visibility graph networks for each province and calculate their degree distributions. Figure 4 shows the power-law distribution of the visibility graph network in Anhui province. From the figure, it can be observed that the degree distribution in Anhui province roughly follows a power-law distribution, indicating that the search data for “professional competency” in Anhui province possesses scale-free characteristics.

Table 2 presents the power-law distributions and fitting quality for the visibility graph networks in various provinces. Here, Y represents the power-law exponent, and R represents the fitting quality. The power-law exponent Y reflects the steepness of the degree distribution, while the fitting quality R indicates the degree of fit between the actual data and the power-law distribution.

TABLE 3 National (excluding Hong Kong, Macao and Taiwan regions) visibility network parameters.

	Overall	2018–2021	2019–2022	2020–2023
Average degree	23.663	21.884	22.037	23.755
Diameter	4	4	4	4
Average path length	1.995	1.997	2.000	1.988
Density	0.024	0.034	0.030	0.034
Average clustering coefficient	0.754	0.790	0.771	0.727

TABLE 4 Community division.

Time	2018–2021	2019–2022	2020–2023
Number	6	10	8

From the table, it can be observed that the power-law exponent Y values for various provinces range from 0.8 to 1.4, indicating that the degree distributions in these provinces follow a power-law distribution. The values of fitting quality R range from 0.3 to 0.6, suggesting a relatively good fit between the actual data and the power-law distribution. Notably, Shandong province stands out with a power-law exponent of 1.415, significantly higher than other provinces, indicating a more pronounced scale-free characteristic in the "professional competency" search data for Shandong province. In contrast, Sichuan province has a lower power-law exponent of 0.798, indicating a lower degree of fit between the data and the power-law distribution.

In summary, the construction and analysis of visibility graph networks for "professional competency" search data in various provinces have revealed scale-free and fractal characteristics in these datasets. This provides strong theoretical support for further research on the awareness to "professional competency."

5.3 Regional system clustering

This study utilizes the parameters of the visibility graph networks for clustering and employs hierarchical clustering to categorize the 31 provinces and regions (excluding Hong Kong, Macau, and Taiwan). Figure 5 displays the clustering results, where each node represents a pair of clusters, the vertical axis length between two nodes indicates the distance between the merged clusters, and the provinces or regions under each category exhibit similar changes in professional competency awareness.

From Figure 5, it can be observed that categorizing the 31 provinces and regions (excluding Hong Kong, Macau, and Taiwan) into 4 groups is optimal. Xinjiang, Yunnan, and Guangxi are grouped together, referred to as the first group; Guizhou, Ningxia, Fujian, Heilongjiang, Hubei, Jiangsu, Zhejiang, Hunan, Shanxi, Gansu, Jiangxi, Hainan, Inner Mongolia, and Anhui form the second group; Qinghai, Tibet, Shanghai, Tianjin, Chongqing, Beijing, Henan, Sichuan, and Guangdong make up the third group; Jilin, Liaoning, Hebei, Shanxi, and Shandong constitute the fourth group.

The Baidu search index for professional competence can to some extent reflect the characteristics of changes in the awareness to professional competence in that province or region. The first and fourth groups have larger network diameters, fewer edges, lower average degrees, clustering coefficients, and densities, indicating weaker relationships among nodes and relatively less emphasis on professional competency education. The second group of provinces and regions falls in between, showing intermediate values for network diameter, edges, average degree, clustering coefficient, and density, suggesting a moderate level of interconnectedness among the nodes. The third group, which includes regions like Shanghai, Chongqing, and Beijing, exhibits higher values for network edges, average degree, clustering coefficient, and density, signifying strong relationships among nodes and high levels of interest in professional competency.

6 Empirical analysis of national data

6.1 Construction of visibility graph networks for professional competency awareness

In order to comprehensively analyze the characteristics of the time series of professional competency awareness, this section uses the principle of visibility graph algorithms to construct visibility graph networks for the nationwide and local Baidu search index time series data for "professional competency" from 2018 to 2023 (as there were no data for 2017). The time series data are divided into 4-year windows, each containing 1,207 nodes, to build local visibility graph networks. These windows are moved forward by 1 year at a time, as shown in Figure 6.

The moving time window principle is a commonly used method in time series analysis, particularly when trying to capture short-term dynamic changes within long time series. This method aids in gaining a better understanding of the characteristics and trends of data during different time periods [40]. By selecting a 4-year time window, at any given time point, the window encompasses data from the past 4 years. Since there are 365 days in a year (ignoring leap years), each window contains

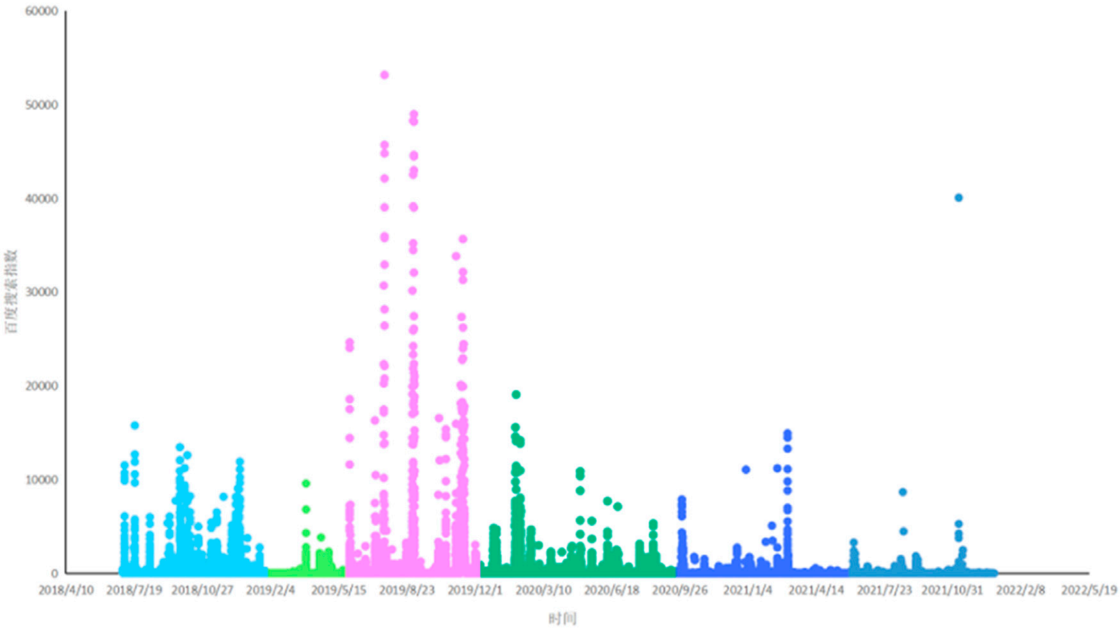

FIGURE 7
Community division of visibility networks in 2018–2021.

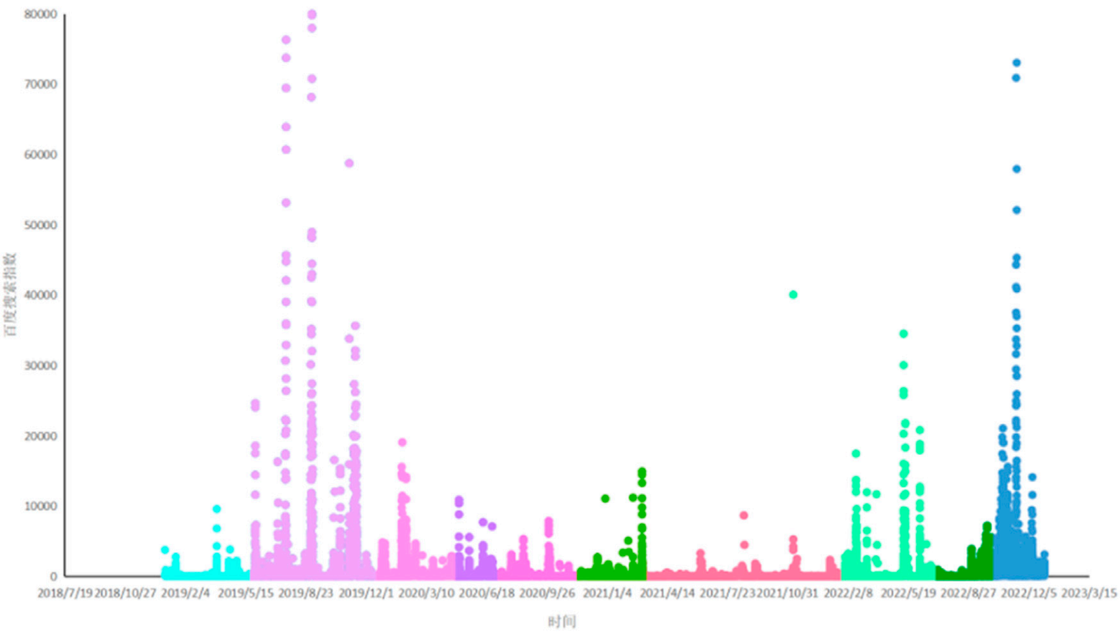

FIGURE 8
Community division of visibility networks in 2019–2022.

1,207 nodes. When the window is moved, it shifts back by 1 year. This means that the first window includes data from 2018 to 2021, the second window includes data from 2019 to 2022, and so on.

This approach allows for the analysis of each 4-year time period to capture the changes and trends in the Baidu search index for "professional competency" during these intervals. As shown in Table 3, Furthermore, because the windows move continuously, it enables the observation of transitional effects and changes between years. The moving time window principle permits local analysis within a long time series, facilitating a better understanding of both short-term and long-term data trends [42].

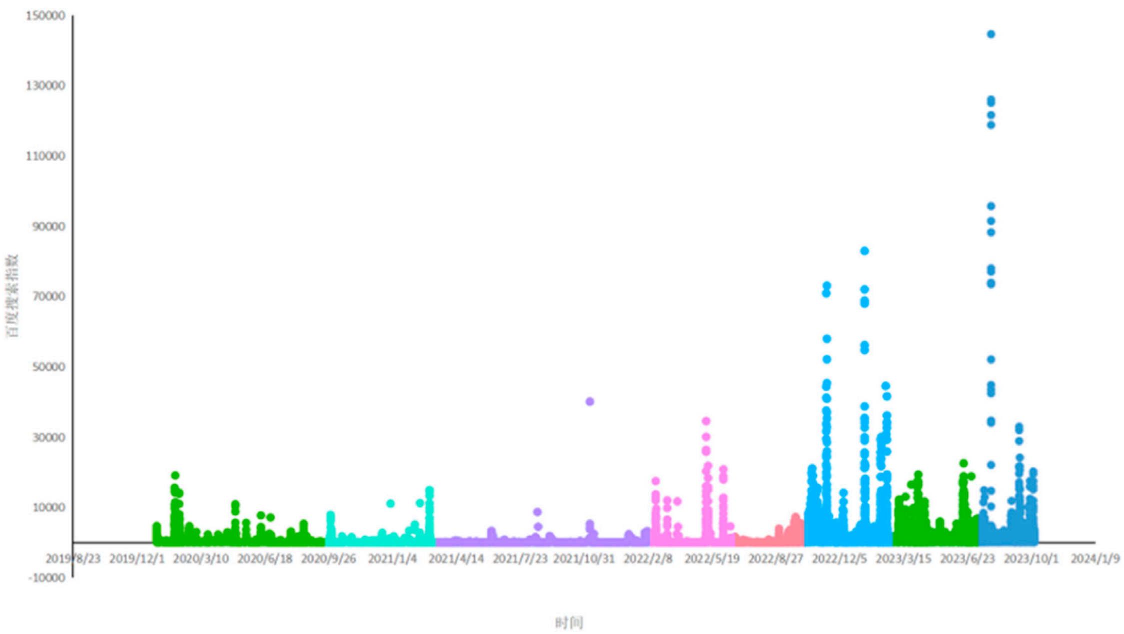

FIGURE 9
Community division of visibility networks in 2020–2023.

6.2 Community structure

In each time window, this study used the Girvan-Newman algorithm to detect the community structure within the visibility graph network [43, 44]. The results of community detection are shown in Table 4; Figures 7–9. Different colors in the figures represent different communities to which nodes belong. As observed in Table 4, the number of communities in the first and third windows is relatively close, indicating that the factors affecting the awareness to patent applications in these two time periods are similar. The second window has 10 communities, suggesting that a stronger influencing factor appeared during the second time window, causing other factors to have less influence and resulting in more data being grouped into one community.

7 Conclusion

This study has conducted an in-depth analysis of the Baidu Index consultation search index to explore the interest levels in “professional competence” across various provinces in China, along with their time series characteristics. The data, sourced from Baidu, spans nearly 6 years, offering both macro and micro perspectives to observe the interest in “professional competence.”

By applying the visibility graph algorithm, we have transformed time series data into a complex network that describes the fluctuations in interest in professional competence over time. This transformation method has provided us with a novel angle to understand the data and has aided us in capturing both the short-term and long-term trends in interest. Additionally, we have explored whether the search data on professional competence in various provinces exhibit scale-free and fractal characteristics, providing robust theoretical support for further research.

Through systematic clustering of the data from each province, we have discovered significant disparities in interest levels in professional competence among different provinces. These variations may be related to the economic development, cultural backgrounds, and educational resources of each province. Moreover, we have identified the time window shift principle in interest in professional competence, which offers us an effective tool for capturing dynamic changes in the data.

Based on these insights, we propose three strategic recommendations for educators and policymakers:

Developing Unique and Tailored Educational Programs. Tailoring educational initiatives to align with the specific needs and interests of each province, taking into account their unique economic, cultural, and educational contexts, will enhance the relevance and impact of these programs.

Data-Driven Dynamic Curriculum Development. Utilizing real-time data analytics, such as those employed in this study, can assist in continuously updating and adjusting educational curricula and policies to meet both current and future competency needs.

Balancing Short-term and Long-term Educational Strategies. It is imperative to design educational and policy strategies that not only address immediate skill gaps but also foresee and prepare for future trends in professional competency.

In summary, this study offers a novel and comprehensive perspective on the interest in professional competence across China. The insights gained are intended to guide educators and policymakers in developing more effective and responsive educational strategies, thereby fostering a workforce well-equipped to meet the demands of the modern professional landscape.

This study also has certain limitations. The data source is limited to Baidu Index, which restricts the breadth and depth of the analysis. Additionally, there are limitations in the visibility graph network in accurately identifying and interpreting the complex dynamics behind these network structures. Although the study identified differences among different provinces, there is a lack of in-depth analysis regarding the specific reasons behind these differences and their concrete impacts on the attention to professional competencies. Future recommendations include strengthening the diversity and richness of data sources by incorporating more social, economic, and educational background data to enhance the accuracy and comprehensiveness of the research. Furthermore, it is suggested to develop more advanced analytical tools and methods to better understand and interpret the dynamic changes behind complex network structures and the specific impacts of these changes on the attention to professional competencies. Additionally, further research is needed to explore the specific reasons for differences in the attention to professional competencies among different regions and to investigate how policy interventions and educational resource allocation can improve the level of professional competencies in areas with low attention, thus providing strategic recommendations for achieving balanced development in vocational education.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving humans were approved by the Yunnan Provincial Department of Education. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

SM: Writing–original draft. LH: Writing–review and editing. PM: Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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