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RESEARCH

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Research on influencing factors of artificial intelligence multi-cloud scheduling applied talent training based on DEMATEL-TAISM

Yi-jie Bian, Lu Xie* and Jing-qi Li

Abstract

With the rapid development of Internet of Things (IoT) technology and the rising popularity of IoT devices, an increasing number of computing intensive IoT applications have been developed. However, due to the limited resources of IoT devices, cloud computing systems are required to compute intensive IoT applications. Furthermore, to be subject to a single cloud computing service provider, multi-cloud computing has become an IoT service cloud computing solution. As a result of the complexity of multi-cloud scheduling, the application of artificial intelligence is an important technology to solve IoT multi-cloud scheduling. The corresponding talent training plays an important role in the development and implementation of the IoT artificial intelligence multi-cloud scheduling. First, this paper studies the key influencing factors of IoT artificial intelligence multi-cloud scheduling applied talent training. Combined with the characteristics of the development of China's artificial intelligence industry, this paper summarizes the influencing factors from the four-dimensional training path of government departments, universities, enterprises and scientific research institutes. The purpose of artificial intelligence multi-cloud scheduling applied talent training is to build an artificial intelligence multi-cloud scheduling applied talent training influencing factor index system. Then, the DEMATEL method is used to establish multiple correlation matrices according to the direct influence correlation between the factors and calculate the degree of influence, the degree of being influenced, the center degree and the cause degree of the factors. Using the improved AISM method, based on the idea of game confrontation, from the two opposite extraction rules of result priority and cause priority, a group of confrontation level topological maps with comprehensive influence values reflecting the interacting factors are obtained, and relevant suggestions are presented to provide a reference for the training of artificial intelligence multi-cloud scheduling applied talent.

Keywords: Internet of things, Multi-cloud scheduling, Applied talent, Personnel training, DEMATEL-TAISM

Introduction

In recent years, the development of IoT-related technologies has gradually increased the application of IoT scenarios in production and life [1]. With the continuous expansion of the application scenarios of the IoT and the rapid development of the commercial landing process of the IoT, on the one hand, the demand for artificial intelligence-related technical support of the IoT has increased sharply [2]; on the other hand, the demand for more resources has also grown [3], and a single cloud service provider can no longer meet the customers' needs. In a multi-cloud environment, different service providers provide more heterogeneous resources to complete the tasks submitted by cloud customers [4]. Therefore, the design of a task scheduling scheme in a multi-cloud environment, that is, efficient resource management, is a challenging problem [5–8]. In the face of this challenging problem, the demand for technical talent related to artificial intelligence multi-cloud scheduling is rising, which further leads to changes in the post setting,

*Correspondence: xie_lu97@163.com

Institute of Management Science and Information Management, Business School, Hohai University, Nanjing 211100, PR China

talent demand and employment situation in the labor and employment markets. Therefore, for the global artificial intelligence competition, talent competition is the core content. The ability and level of talent training have an important impact on the development of the national artificial intelligence industry. The rapid development of artificial intelligence technology is bound to bring about profound changes in talent training. Training relevant talent is not only to teach the knowledge and technology related to artificial intelligence but also to cultivate comprehensive and all-round applied talent that meet the needs of society [9–11].

Aiming at the research of information technology, such as artificial intelligence, the Internet of Things, and cloud computing, Yan explained that due to the increasing demand for cloud real-time computing and the enormous amount of data generated through the Internet of things, traditional cloud infrastructure devices have long delays and other limitations. Mobile edge computing has become a prominent network architecture to solve such problems [12]. Li made a comprehensive and detailed review of the concept of the Internet of Things and then elaborated on the scientific development of the Internet of Things supported by remote technology [13]. Catlett and Tong showed that artificial intelligence can realize remote "edge" measurement of urban data factors, which affected smart city construction [14, 15]. Dong took the Internet of vehicles in typical scenes in the edge information system as the core, takes the relevant model of distributed machine learning as an example, considers the relevant problems in worker selection, and finally proposes a solution based on deep reinforcement learning (DRL) [16]. Sandhu and Chen indicated that big data is an important research field. Cloud computing provides a cost-effective and scalable solution for storing big data and elaborates on the relationship between big data and cloud computing [17, 18]. Kim discussed that based on the development of the Internet of Things, people are increasingly dependent on cloud service providers [19].

Due to the impact of relevant information technology on education and human resources, Grover, Chen and Huang et al. showed that, because of the strong comprehensibility and applicability of artificial intelligence, the demand for artificial intelligence compound talent in new positions is strengthened, which imperceptibly promotes the exploration and reform of innovative talent training modes in higher education institutions. It also promoted the transformation of engineering talent training to the goals of intelligence, automation, humanization and precision [20–23]. Wang et al. argued that although the development of artificial intelligence would replace the existing jobs' effect, it would also create new jobs and employment opportunities for the talent market and improve job quality as in the market in recent years, artificial intelligence algorithm engineers, data architects, artificial intelligence product managers, and other high-end technical talent positions [24]. Jun studied training human resource management professionals in the context of artificial intelligence [25]. Liu et al. practiced and explored management accounting talent training in a background of big data and artificial intelligence to integrate big data, artificial intelligence, cloud computing and other information technologies and promote professional informatization into a new stage [26]. Feng steadily integrated artificial intelligence into the mode of translation talent training, greatly innovating the concepts and methods of college English translation teaching in China to continuously improve the quality of talent training [27]. Oberc and Chen discussed practical learning methods in factories and the possibility of bringing artificial intelligence closer to workers by teaching supervised machine learning training [28, 29]. Zhai integrated big data into the education field, and the proposed "Multi AFM" model provides a new method for teaching evaluation [30]. Wang et al. presented the demand analysis of artificial intelligence talent, indicating that applied talent is at the bottom of the artificial intelligence talent system, but the number is the largest, which is the indispensable foundation for artificial intelligence practice [9].

At present, the training of artificial intelligence talent in China still lags behind the international level, and thus, research on artificial intelligence talent training is essential. In 2018, the Ministry of Education officially presented the interdisciplinary talent training mode of "artificial intelligence+X", which promoted the specialty setting of "new engineering" disciplines and influenced its future development trend. Fang demonstrated that, led by iFLYTEK, technology and internet giants, such as Tencent, Baidu, and Huawei, have carried out joint talent training with some colleges and universities in China and jointly established the School of Artificial Intelligence, the Institute of Artificial Intelligence, Laboratories, etc., to train artificial intelligence professionals that enterprises truly need [31]. Zhao et al. emphasized the dilemma of the reform of the higher education talent training mode in the era of artificial intelligence: the evaluation system of higher education talent training is relatively backward, and the improvement of the evaluation system of higher education talent training needs to be promoted in an orderly manner [32]. Geng et al. expounded that world-class universities should focus on training artificial intelligence talent with a broad base and wide caliber, attaching importance to the training of artificial intelligence talent's practicability, and attaching importance to the training of artificial intelligence talent' interdisciplinary ability [33].

In summary, it was found that domestic and foreign scholars' research on artificial intelligence and applied talent training are independent of each field. Most of them start from the application and development of artificial intelligence in traditional disciplines or industries and focus more on discipline or industry construction. Even if there are studies related to artificial intelligence talent training, they are all broad descriptions of industry talent training and have not been refined to artificial intelligence application talent. Research on the influencing factors of talent training in artificial intelligence has been constantly optimized with the development of the economy and society. Most of the previous studies only drew on a single perspective and did not detail applied talent. Most of the research methods were qualitative research, but few were quantitative research. At this stage, there are few studies on training applied talent in multi-cloud scheduling under the background of artificial intelligence, and they all stay at the theoretical level. Few articles interpret the influencing factors of the training of applied talent in multi-cloud scheduling of artificial intelligence in China from the perspective of actual data, mathematics or combined with models. At the same time, the DEMATEL method and the AISM method have not been applied to research on the training of applied talent in multi-cloud scheduling of artificial intelligence.

The main work presented in this paper is summarized as follows:

1) By combining the existing empirical research conclusions and through expert interviews and questionnaires, we built a system of influencing factors for the training of AI multi-cloud scheduling applied talent.
2) We improve the AISM method to form the TAISM method with a comprehensive influence value. That is, based on the AISM method, the value of 1 in the general skeleton matrix s is replaced by the comprehensive influence value.
3) Combined with the DEMATEL method and the TAISM method, we analyze the hierarchical structure and relationship between the influencing factors from multiple perspectives, such as the causal relationship between factors and the integration of the idea of game confrontation, to provide a basis for the government to formulate policies and promote the rapid development of the artificial intelligence industry. At the same time, it has theoretical reference importance and application value for the scheduling problem and talent training in the cloud environment.

The rest of this paper is arranged as follows: Section 2 is the introduction of concepts and the construction of influencing factors. In Section 3, we describe the selection of the model and list the model's calculation steps. In Section 4, the results of the model are discussed, and the application analysis is carried out. Finally, we present a summary of the paper and make suggestions according to the analysis of the results. The research flow chart of this paper is displayed in Fig. 1.

Concept definition and influencing factors

Multi-cloud scheduling

Multiple clouds include multiple independent clouds, which are not connected voluntarily and are not shared with virtual resources [34]. Therefore, in such an environment, it is the customer's responsibility to manage the supply and scheduling of virtual resources. In this case, customers can access the multi-cloud environment by using services hosted externally or internally by the cloud client [35]. Compared with the traditional single cloud environment, the multi-cloud environment has the following advantages: performance guarantee, meaning that service performance can be maintained by using resources from other cloud service providers in the multi-cloud; availability, which refers to the geographical distribution of different service providers in a multi-cloud environment that allows the migration of businesses, virtual machines and data and improves the availability of businesses [36]; diversified customer needs, which means that maintaining customer satisfaction is very important to improve customer experience, and the heterogeneous nature of different service providers offers customers diversified services; regional workload meaning that due to geographical dispersion, the workload can be redirected to the cloud closer to the customer [37]; convenience through the unified visualization of various available services as it provides customers with the convenience of relevant services. To meet the business needs during peak hours and more effectively deal with massive data problems, the optimization of task scheduling performance in a multi-cloud environment can better meet the needs of customers and service providers. Therefore, training applied talent for multi-cloud scheduling is also the current development trend [38] (Fig. 2).

Applied talent

According to China's national conditions, the classification scheme of colleges and universities in UNESCO's "International Standard Classification of Education" is in line with the current situation of China's education and talent structure and is more likely to be recognized by people [39, 40]. As a part of the plan, colleges and universities are divided into academic research-oriented universities, which are devoted to training academic innovation and research theory-related talents, skilled colleges and

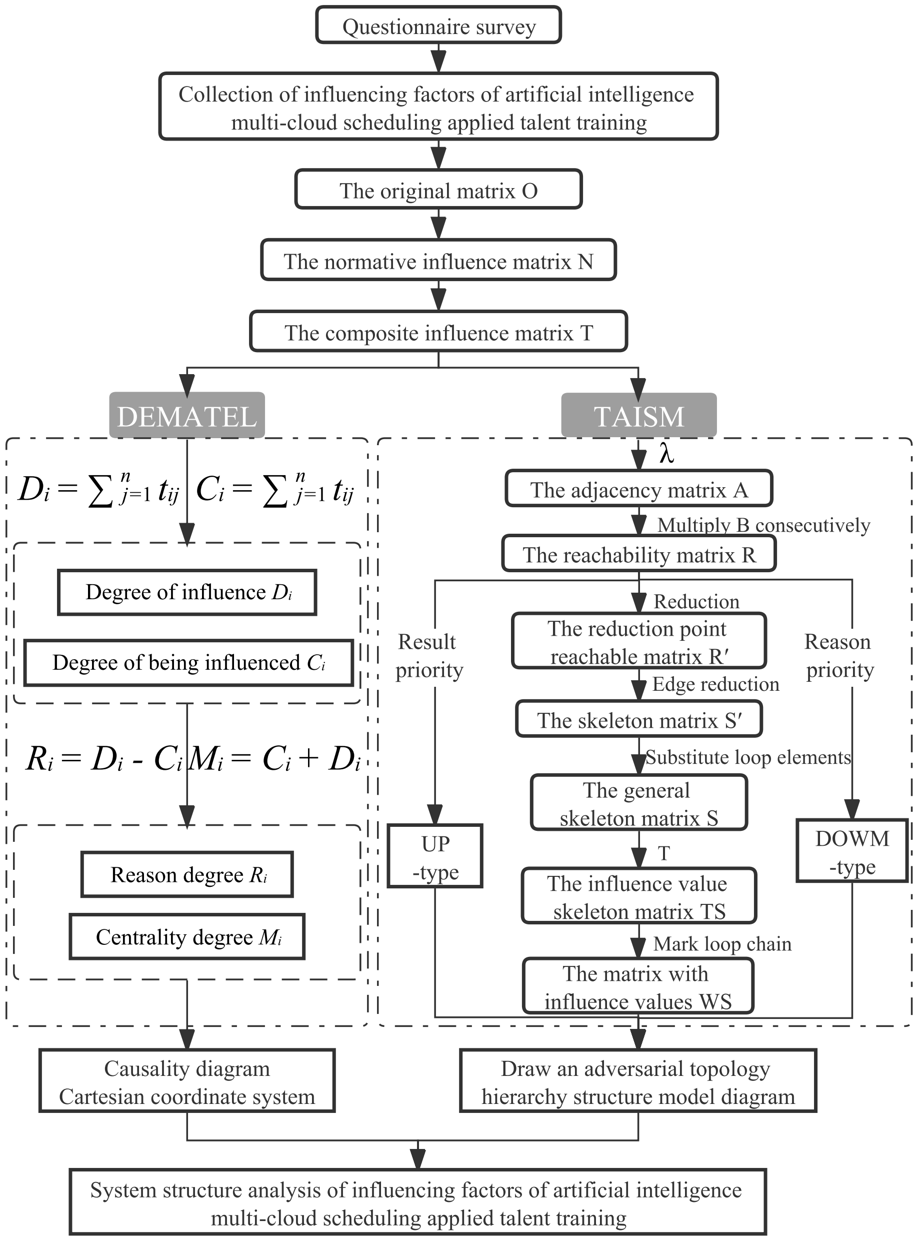

Fig. 1 Research flow chart

universities (higher vocational colleges), which are dedicated to training talent related to crafts, practical operations, and technical industries and application-oriented universities, which are effective in training between academic research-oriented and skill-oriented, adapting to the development needs of majors and industries. The school is more practical and comprehensive. We refer to the talent trained by these three types of colleges as research talent, skilled talent and applied talent accordingly. From the above three types of talent, it can be seen that the training of multi-cloud scheduling applied talent achieves “specialization and practicality” and “theoretical research”, which complement each other and pays attention to “the comprehensive ability and practicability to comprehensively apply theoretical knowledge and methods to solve practical problems” [41].

Construction of the influencing factor system

Based on the existing domestic and foreign research results and the development status of applied talent

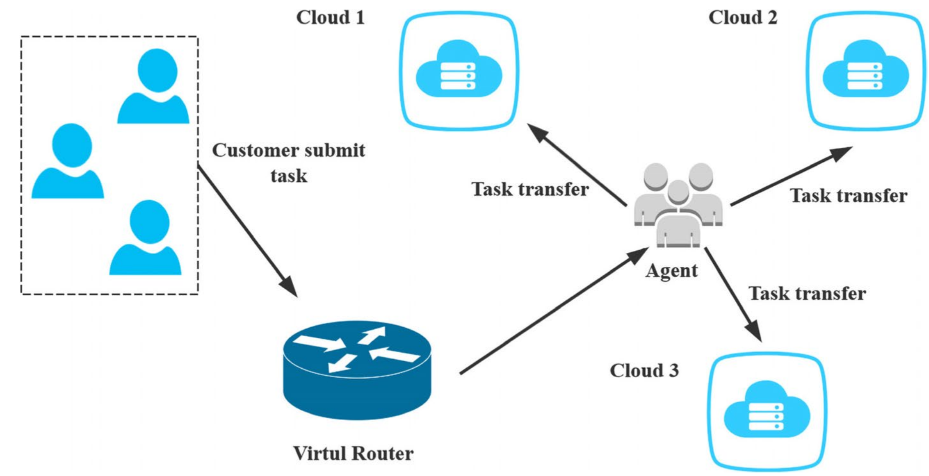

Fig. 2 Task scheduling process in a multi-cloud environment

training at home and abroad, focusing on the needs of artificial intelligence and multi-cloud scheduling, the potential influencing factors of applied talent training in the artificial intelligence multi-cloud scheduling industry are summarized from the four-in-one multidimensional training path of government departments, universities, enterprises and research institutes (politics, education, production and research) [42–45]. Through the questionnaire investigation and expert consultation method changes, the index system is continuously optimized, and finally, artificial intelligence multi-cloud scheduling is qualitatively identified by applying a talent training index system of influencing factors.

Colleges and universities determine the trend of talent training to a certain extent, and the professional degree of faculty structure is a key factor in the process of talent training. At the same time, in this paper, the factor of training base construction and education integration is regarded as a college-level factor to facilitate research and finally summarizes four factors at the level of colleges and universities. As the most important influencer in training multi-cloud scheduling applied talent, enterprises can coordinate the reasonable operation of other parties in the demand and management of artificial intelligence talent. Mainly through the management and development system of talent within the enterprise and the training promotion and incentive mechanism to strengthen the effective promotion of talent training, we finally summarize five factors at the enterprise level. The degree of social support for the artificial intelligence industry is related to the efficient and rapid development and implementation of the training work at the level of universities and enterprises. It affects the training and development intention of colleges and individuals to a great extent and summarizes five factors at the social level. Talent training is a complex system where the characteristics of talent itself are an indispensable factor. Finally, four factors at the personal level are summarized. According to the above analysis, the influencing factors of artificial intelligence multi-cloud scheduling applied talent training mainly come from four levels: colleges, enterprises, society and individuals, including 21 factors, such as the investment cost of enterprise applied talent training, the proportion of industrial investment in GDP and the height of career goals [46–50] (see Table 1 for details).

Construction of the DEMATEL-TAISM model

Training applied talent in artificial intelligence multi-cloud scheduling is a system of complex factors. When studying the training of applied talent, we need to comprehensively consider various factors and consider the interaction between the factors in the system. In this way, the calculated results can achieve the purpose of treating both symptoms and root causes and continuous improvement. Traditional analytic hierarchy processes, factor analysis, principal and component analysis cannot consider the relationship between complex factors in the system. In recent years, some experts and scholars have integrated and applied a variety of mathematical models to avoid the above problems. Among them, the method of combining the DEMATEL method and the ISM method is currently developing rapidly and has been frequently used in recent years. These methods can consider the interaction between indicators in the process of practical application.

Table 1 Index System of influencing factors for training applied talent of artificial intelligence multi-cloud scheduling

Indicator classification	First-level index	Second-level index
Affecting factor system of artificial intelligence multi-cloud scheduling applied talent training	A1: College level	B11: Professional degree of teacher structure
		B12: Experimental equipment and technical capabilities
		B13: Practical training base construction and education integration degree
		B14: Professional re-education intensity
	A2: Enterprise level	B21: Talent management and development system
		B22: Applied talent training investment cost
		B23: Corporate social responsibility
		B24: Degree of participation in industry-university-research education
		B25: Training promotion and incentive mechanism
	A3: Social level	B31: Supportive Policy and Strategic Impact
		B32: Special fund reward and subsidy standard
		B33: Artificial intelligence major and School evaluation
		B34: Industry R&D and innovation support
		B35: Proportion of industrial investment in GDP
	A4: Individual level	B41: Individual characteristics
		B42: Career goals height
		B43: Innovative self-efficacy
		B44: Awareness of industry and corporate standards

Model selection

Huang argue that ISM is one of the important methods in educational technology research. Based on hacker and anti-hacker thinking, he proposed five improved ISM methods and elaborated on them in detail, bringing enlightenment to the application and expansion of the ISM model [51]. Zhou and Zhang proposed the integration of DEMATEL/ISM to construct a system hierarchy and provided the theoretical basis and algorithm of method integration. Effective integration of the DEMATEL/ISM method can reduce the computational amount and complexity of reachable matrices, providing a new idea for the analysis and decision-making of complex systems [52]. Xie first proposed the adversarial interpretation structural model method, the AISM method. This study uses the TOPSIS-AISM to analyze 8 evaluation objects and 19 dimensions of indicators and finally uses four sets of hierarchical topological maps to indicate the entire evaluation process [53].

We found that in the previous application of the ISM method and the AISM method, only the multilevel hierarchical structural diagram of the subject index is obtained. Through the structural diagram, we can only see the hierarchical structure and correlation of the index, but we cannot see the impact of the correlation between the indices, resulting in an unclear display structure of the model. Based on the above method, this study adds the comprehensive influence value, namely, the TAISM method, on the basis of AISM. The TAISM method combines the comprehensive influence value between indicators with the extraction results of confrontation levels and displays the results of the improved method by drawing a group of directed topological hierarchical structural diagrams with comprehensive influence values. This structural diagram enables the relevance and influence degree of each indicator in the influencing factor system to be more clearly displayed, which is conducive to the analysis of the model's results.

Based on the above influencing factor system of applied talent training of artificial intelligence multi-cloud scheduling, we first calculate the matrix through the DEMATEL method to obtain the degree of influence, degree of being influenced, degree of cause and center of each factor. Combined with the causal relationship diagram of factors, the key influencing factors of artificial intelligence multi-cloud scheduling applied talent training are identified. The comprehensive influence matrix calculated by the DEMATEL method can directly calculate the reachable matrix. According to the reachable matrix and the TAISM method, a set of adversarial directed topological hierarchy graphs with comprehensive influence values can be obtained. Therefore, the combined use of the DEMATEL-TAISM model can identify and evaluate key factors in complex systems and clarify the structural levels of factors in the system.

DEMATEL method

Build the original matrix O

Through questionnaires and interviews, experts are asked to quantify and score the mutual influence relationship among the factors in the multidimensional index system affecting the training of artificial intelligence multi-cloud scheduling applied talent, where 0 means that there is no influence, 1 means that there is a weak influence, 2 means there is a general influence, 3 means that there is a strong influence and 4 means that there is a stronger influence. The research objects involved in expert fields include 3 professors and associate professors of artificial intelligence in applied universities, 2 personnel and senior executives of artificial intelligence companies, and 1 practitioner in the artificial intelligence industry. After all the expert scoring forms are recovered, the scores are summarized, and the sum of quantitative influence relationships in the six scoring forms is calculated. Determining the relationship between factors and the relationship between the direct influence degree $S_i(i=1,2...18)$ and $S_j(j=1,2...18)$ is represented by o_{ij}, o_{ij} is the strength of the influence of the i factor on factor j, and $O(o_{ij})_{18\times18}$ is the direct influence matrix.

Calculate the composite influence matrix T

We normalize the direct influence matrix O by the row sum maximum method to obtain the normative influence matrix N, and the calculation process is shown in Formula 1 as follows:

$$N=\left(\frac{o_{ij}}{Maxvar}\right)_{18\times18} \tag{1}$$

where $Maxvar=\max\left(\sum_{j=1}^{n}o_{ij}\right)$.

Using the obtained standardized influence matrix and Formula (2), the comprehensive influence matrix T of the influencing factors of artificial intelligence multi-cloud scheduling applied talent training is obtained, that is, $T=(t_{ij})_{18\times18}$.

$$T=N+N^2+N^3+\cdots+N^k=\sum_{k=1}^{\infty}N^k\rightarrow T=N(I-N)^{-1} \tag{2}$$

where I is the identity matrix and A is the inverse matrix of B. From this, the composite influence matrix T can be seen in Table 2.

Calculate the degree of influence D_i and the degree of being influenced C_i

Based on the comprehensive influence matrix T, the degree of influence D_i can be obtained by accumulating the values of the rows, and the degree of being influenced C_i of each factor can be obtained by accumulating the values of the columns as follows:

$$D_i=\sum_{j=1}^{n}t_{ij},1\leq i\leq n \tag{3}$$

$$C_i=\sum_{j=1}^{n}t_{ji},1\leq i\leq n \tag{4}$$

Table 2 Composite influence matrix *T*

	$M_{18\times18}$	B11	B12	B13	B14	B21	B22	B23	B24	B25	B31	B32	B33	B34	B35	B41	B42	B43	B44
T=	**B11**	0.052	0.118	0.133	0.153	0.132	0.193	0.11	0.149	0.082	0.055	0.104	0.135	0.108	0.094	0.149	0.18	0.168	0.147
	B12	0.087	0.055	0.115	0.085	0.071	0.104	0.078	0.101	0.049	0.034	0.05	0.119	0.11	0.072	0.101	0.122	0.123	0.104
	B13	0.084	0.112	0.069	0.104	0.098	0.127	0.104	0.137	0.067	0.048	0.08	0.112	0.123	0.082	0.106	0.138	0.137	0.118
	B14	0.036	0.086	0.084	0.062	0.099	0.124	0.096	0.121	0.088	0.033	0.053	0.08	0.089	0.065	0.131	0.155	0.139	0.127
	B21	0.081	0.111	0.142	0.141	0.107	0.198	0.135	0.187	0.159	0.067	0.069	0.127	0.15	0.11	0.191	0.244	0.224	0.202
	B22	0.099	0.156	0.172	0.193	0.191	0.152	0.134	0.203	0.139	0.093	0.097	0.133	0.207	0.154	0.191	0.247	0.225	0.209
	B23	0.05	0.064	0.094	0.099	0.12	0.155	0.066	0.133	0.113	0.081	0.079	0.07	0.135	0.101	0.12	0.147	0.112	0.163
	B24	0.074	0.114	0.129	0.117	0.138	0.184	0.132	0.098	0.098	0.071	0.079	0.099	0.139	0.108	0.132	0.185	0.143	0.17
	B25	0.061	0.094	0.123	0.146	0.15	0.172	0.087	0.128	0.072	0.039	0.046	0.089	0.106	0.085	0.171	0.218	0.209	0.177
	B31	0.102	0.136	0.152	0.166	0.189	0.212	0.161	0.191	0.135	0.067	0.157	0.16	0.212	0.16	0.201	0.251	0.197	0.205
	B32	0.105	0.142	0.159	0.156	0.169	0.189	0.143	0.171	0.131	0.116	0.071	0.152	0.17	0.143	0.165	0.218	0.203	0.166
	B33	0.112	0.144	0.144	0.139	0.134	0.158	0.113	0.137	0.091	0.097	0.125	0.083	0.12	0.104	0.137	0.176	0.155	0.172
	B34	0.076	0.119	0.126	0.131	0.136	0.183	0.111	0.136	0.118	0.089	0.09	0.097	0.096	0.128	0.155	0.196	0.199	0.169
	B35	0.083	0.135	0.128	0.124	0.138	0.201	0.12	0.154	0.116	0.128	0.13	0.112	0.195	0.082	0.14	0.198	0.169	0.193
	B41	0.041	0.074	0.055	0.084	0.095	0.133	0.082	0.084	0.093	0.029	0.034	0.091	0.074	0.052	0.071	0.165	0.158	0.138
	B42	0.037	0.053	0.058	0.077	0.096	0.102	0.062	0.108	0.087	0.025	0.03	0.078	0.052	0.039	0.105	0.085	0.164	0.138
	B43	0.045	0.079	0.091	0.095	0.091	0.122	0.063	0.096	0.086	0.049	0.055	0.096	0.095	0.072	0.122	0.161	0.09	0.133
	B44	0.021	0.048	0.043	0.046	0.065	0.083	0.065	0.077	0.051	0.019	0.029	0.042	0.038	0.029	0.078	0.124	0.096	0.053

Calculate the centrality degree M_i and the reason degree R_i

According to Formula (5), the centrality degree M_i is obtained by adding the degree of influence D_i and the degree of being influenced C_i of each influencing factor. According to Formula (6), the reason degree R_i is obtained by subtracting the degree of being influenced C_i of each influencing factor from the degree of influence D_i as follows (Table 3):

$$M_i = D_i + C_i \tag{5}$$

$$R_i = D_i - C_i \tag{6}$$

TAISM method

Build an adjacency matrix A

Introducing the intercept A, the intercept value in this paper is obtained by statistics with the matrix T, and its calculation formula is as follows:

$$\lambda = \overline{x} + \sigma \tag{7}$$

where A is the mean of the matrix values in the T matrix and B is the sample standard deviation (Table 4).

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n^2} (x_i - \overline{x})^2}{n^2 - 1}} \tag{8}$$

$$O_{ij} = \begin{cases} 1, t_{ij} \geq \lambda = 0.16501710625713 \\ 0, t_{ij} < \lambda = 0.16501710625713 \end{cases} (i, j = 1, 2, 3, ...18)$$

Build the reachable matrix R

For any adjacency matrix A, the reachable matrix R is calculated as follows:

$$B = A + I \tag{9}$$

where B is the multiplication matrix and I is the identity matrix, that is, a Boolean square matrix with only the diagonal value of 1. Then, B is multiplied consecutively as follows:

$$B^{k-1} \neq B^k = B^{k+1} = R \tag{10}$$

From this, the reachable matrix R is obtained, and the result is as follows (Table 5):

Build a general skeleton matrix S

The reduction point is carried out by the reachable matrix R; the loop in the reachable matrix is regarded as a point, which is called the reduction point. After reduction of the point, the reduction points reachable matrix R' is obtained, and then the edge reduction calculation is carried out. The essence of the edge reduction operation is to delete the repeated paths. The method is as follows:

Table 3 Influence and causality table

Factor	D_i	C_i	M_i	**Centrality sort**	R_i	**Positive sort (reason)**	**Negative sort (result)**
B22	2.995	2.791	5.787	1	0.204	8	
B21	2.645	2.219	4.864	2	0.426	6	
B24	2.209	2.411	4.62	3	−0.203		−2
B42	1.394	3.211	4.605	4	−1.818		−8
B34	2.355	2.219	4.574	5	0.135	9	
B43	1.642	2.91	4.552	6	−1.268		−6
B35	2.545	1.679	4.224	7	0.866	4	
B33	2.341	1.875	4.216	8	0.466	5	
B31	3.052	1.14	4.192	9	1.913	1	
B32	2.768	1.378	4.145	10	1.39	2	
B41	1.554	2.468	4.022	11	−0.914		−5
B25	2.173	1.775	3.948	12	0.398	7	
B13	1.846	2.017	3.862	13	−0.171		−1
B44	1.009	2.783	3.793	14	−1.774		−7
B14	1.668	2.119	3.787	15	−0.451		−4
B23	1.903	1.861	3.764	16	0.042	10	
B11	2.261	1.243	3.504	17	1.018	3	
B12	1.581	1.84	3.421	18	−0.259		−3

Table 4 Adjacency matrix A

	$M_{18\times 18}$	B11	B12	B13	B14	B21	B22	B23	B24	B25	B31	B32	B33	B34	B35	B41	B42	B43	B44
A=	**B11**	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0
	B12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B21	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	1	1	1
	B22	0	0	1	1	1	0	0	1	0	0	0	0	1	0	1	1	1	1
	B23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B24	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	1
	B25	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	1	1
	B31	0	0	0	1	1	1	0	1	0	0	0	0	1	0	1	1	1	1
	B32	0	0	0	0	1	1	0	1	0	0	0	0	1	0	1	1	1	1
	B33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
	B34	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1
	B35	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	1	1
	B41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	B42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 5 Reachable matrix R

	$M_{18\times 18}$	B11	B12	B13	B14	B21	B22	B23	B24	B25	B31	B32	B33	B34	B35	B41	B42	B43	B44
R=	**B11**	1		1	1	1	1		1					1		1	1	1	1
	B12		1																
	B13			1															
	B14				1														
	B21			1	1	1	1		1					1		1	1	1	1
	B22			1	1	1	1		1					1		1	1	1	1
	B23							1											
	B24			1	1	1	1		1					1		1	1	1	1
	B25			1	1	1	1		1	1				1		1	1	1	1
	B31			1	1	1	1		1		1			1		1	1	1	1
	B32			1	1	1	1		1			1		1		1	1	1	1
	B33												1				1		1
	B34			1	1	1	1		1					1		1	1	1	1
	B35			1	1	1	1		1					1	1	1	1	1	1
	B41															1	1		
	B42																1		
	B43																	1	
	B44																		1

$$S' = R' - \left(R' - I\right)^2 - I \tag{11}$$

The skeleton matrix S' is obtained by reducing the edge of R', and the general skeleton matrix S is obtained by substituting the loop elements.

Build the matrix with influence values WS

The value of 1 in the general skeleton matrix S is replaced with the comprehensive influence value, that is, the corresponding value in T is replaced to obtain the influence value skeleton matrix TS. We mark the directed edge inside the loop chain with 1 to obtain the matrix with influence value *WS*. *WS* is the matrix with influence values shown in Table 6.

Extraction of adversarial hierarchy

For the reachable matrix, there is reachable set *R*, prior set *Q*, and common set *T*, where $T = R \cap Q$. For example, for the adjacency matrix *A*, the reachable set of e_i is denoted as $R(e_i)$, that is, all elements with a row value that corresponds to 1. The prior set of e_i is denoted as $Q(e_i)$, that is, all the elements with a column value that corresponds to 1. The common set of e_i is denoted as $T(e_i)$, that is, $R(e_i) \cap Q(e_i)$.

For the UP-type topology diagram, the results are prioritized for hierarchical division, and the extraction rules are as follows: $\mathrm{T(e_i)} = \mathrm{R(e_i)}$. As long as the reachable set is the same as the common set, the relevant elements are extracted. The extracted features are placed above each time, and the extracted features are placed in order from top to bottom.

For the DOWN-type topology diagram, the reasons are prioritized for hierarchical division, and the extraction rules are as follows: $T(e_i) = Q(e_i)$. The extracted features are placed below each time, and the extracted features are placed in order from bottom to top.

Extracted according to the above method, the results are displayed in Table 7:

Draw an adversarial topology hierarchy structure model diagram

According to the relationship between elements and the results of the confrontation level extraction, a directed topological hierarchy graph can be drawn. There is a reachable relationship among factors in the system, which is represented by a directed line segment and a two-way arrow to form a loop; they are reachable relationships with each other. At the same time, the lower layer indicates that the influencing factors are rooted, and the higher layer indicates that the influencing factors are direct. The UP-type and DOWN-type topological

Table 6 The matrix with influence values WS

	$M_{18 \times 18}$	B11111	B12	B13	B14	B21	B22	B23	B24	B25	B31	B32	B33	B34	B35	B41	B42	B43	B44
T=	B11	0	0	0	0	0	0.193	0	0	0	0	0	0	0	0	0	0	0	0
	B12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B21	0	0	0	0	0	1	0	1	0	0	0	0	1	0	0.192	0	0.224	0.202
	B22	0	0	0.172	0.193	1	0	0	1	0	0	0	0	1	0	0	0	0	0
	B23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B24	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0
	B25	0	0	0	0	0	0.172	0	0	0	0	0	0	0	0	0	0	0	0
	B31	0	0	0	0	0.189	0	0	0	0	0	0	0	0	0	0	0	0	0
	B32	0	0	0	0	0.169	0	0	0	0	0	0	0	0	0	0	0	0	0
	B33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.176	0	0.172
	B34	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0
	B35	0	0	0	0	0	0.201	0	0	0	0	0	0	0	0	0	0	0	0
	B41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.165	0	0
	B42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 7 Adversarial level extraction results

Level	Result priority——UP-type	Reason priority——DOWN-type
Level 1	B12, B13, B14, B23, B42, B43, B44	B42
Level 2	B33, B41	B13, B14, B41, B43, B44
Level 3	B21, B22, B24, B34	B21, B22, B24, B34
Level 4	B11, B25, B31, B32, B35	B11, B12, B23, B25, B31, B32, B33, B35

hierarchical structural model diagrams are depicted in Figs. 3 and 4.

Application analysis based on the DEMATEL-TAISM model

Centrality degree and reason degree analysis

Centrality degree

The function of the centrality degree is to measure the influence of factors on the whole system. The larger the value of the factor, the more important the factor is and the stronger the impact on the system. According to Fig. 5, we can see that the top five centrality values of the influencing factors of artificial intelligence multi-cloud scheduling applied talent training are applied talent training input cost B22, talent management and development system B21, degree of participation in industry-university-research education B24, career goals height B42, industry R&D and innovation support B34. Therefore, these factors should be focused on and analyzed when regulating the system.

Reason degree

The function of reason degree is to measure the influence of factors on other factors. When $R_i > 0$, this factor is the cause factor. The larger the value of R_i, the greater its influence on other factors. When $R_i < 0$, this factor is the result factor, and the smaller the value of R_i, the greater the degree of its influence by other factors. In this system, the top five positive values of reason degree are corporate social responsibility B23, enterprise R&D and innovation support B34, applied talent training investment cost B22, training promotion and incentive mechanism B25 and talent management and development system B21. Factors are mainly distributed at the enterprise level and the

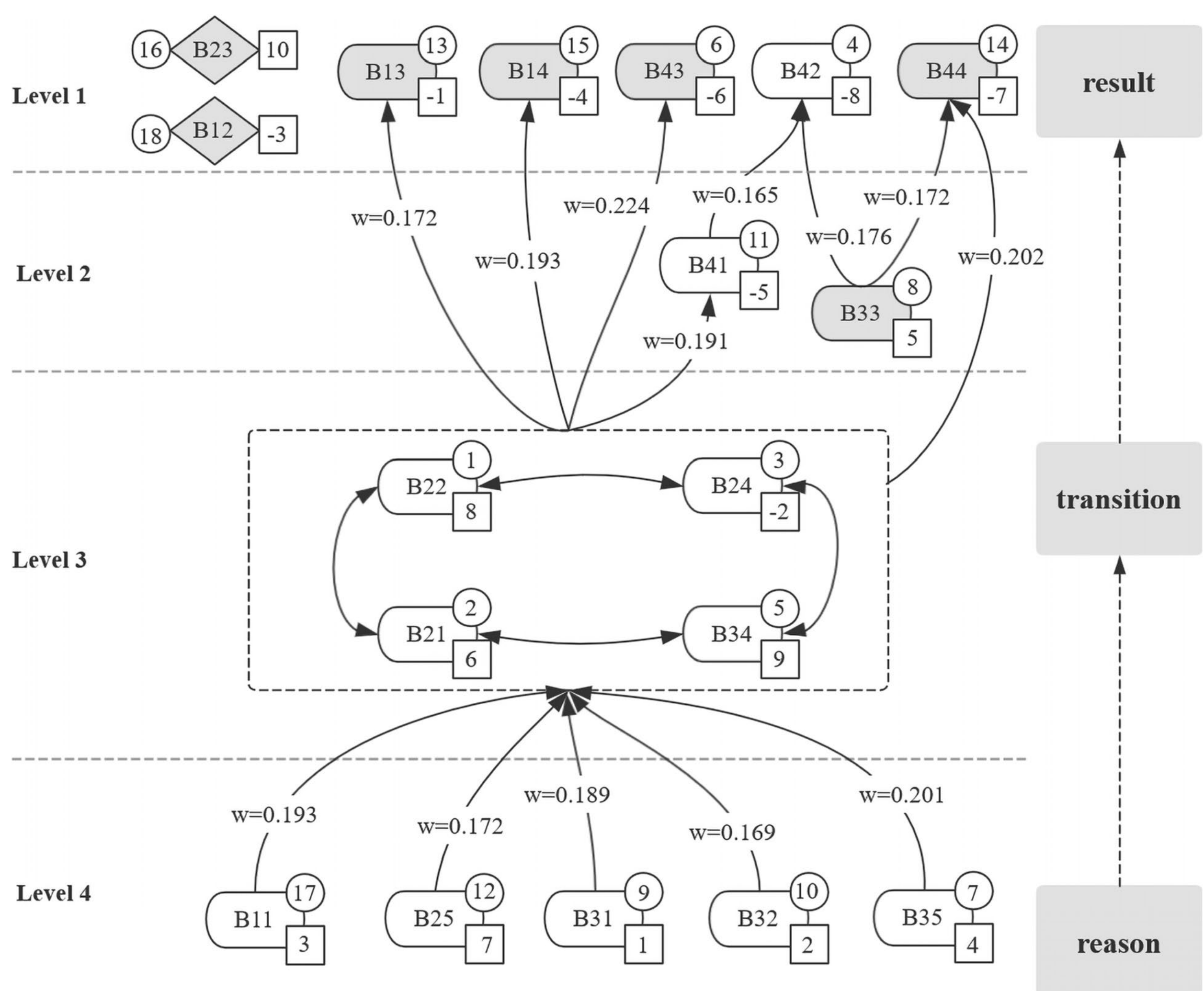

Fig. 3 UP-type topological hierarchical structural model diagram

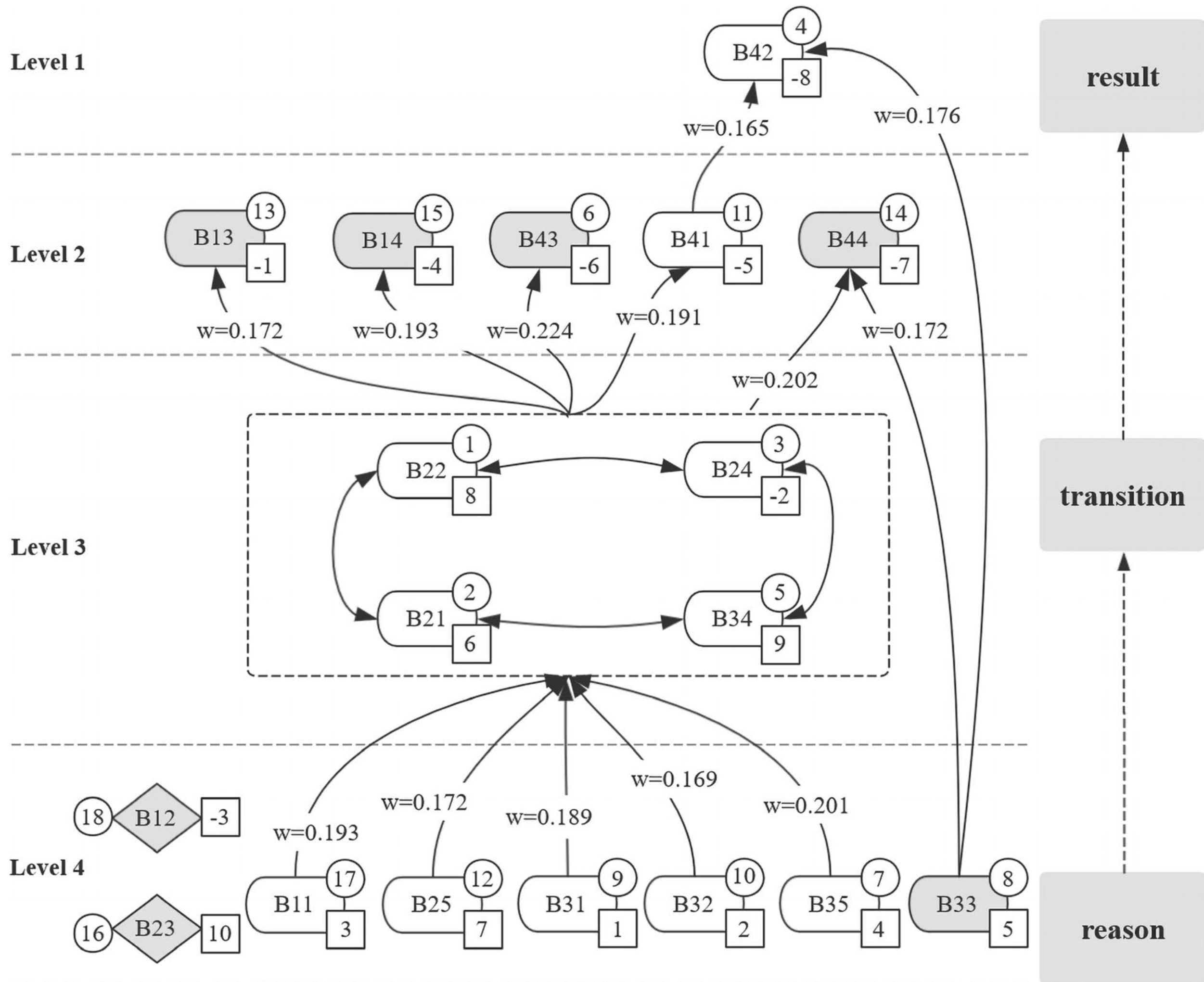

Fig. 4 DOWN-type topological hierarchical structural model diagram

social level, indicating that they are more likely to have an impact on the training of artificial intelligence multi-cloud scheduling applied talent. Therefore, we should pay attention to the regulation of these factors.

In the system, the top five negative values of causation degree from small to large are career goal height B42, awareness of industry and corporate standards B44, innovation self-efficacy B43, individual characteristics B41, and professional re-education intensity B14. We found that the four factors at the individual level are all outcome factors meaning that they are strongly influenced by other factors, which is also consistent with our expected cognition. When regulating these factors, we should focus on other related factors.

Analysis of extensible active systems

In the topology hierarchy model diagram, if a factor is at different levels in the UP-type topology diagram and the DOWN-type topology diagram, it is called an active factor. A system with active factors is called an extension variable system and is also called an active system; a system without active factors is called a rigid system, also known as a topologically rigid system. In the system shown in the above figure, the gray marked factors B12, B23, B13, B14, B43, B44 and B33 are transitions between different levels, so they are activity factors. Research on the influencing factors of artificial intelligence multi-cloud scheduling applied talent training is an extension variable system.

Isolated factor analysis

Factors B12 and B23 represented by diamonds in the topology hierarchy model diagram are isolated factors. It can be seen from the topology diagram that B12 and B23 have no directed line segment representation with other factors in the system; that is, there is no influence

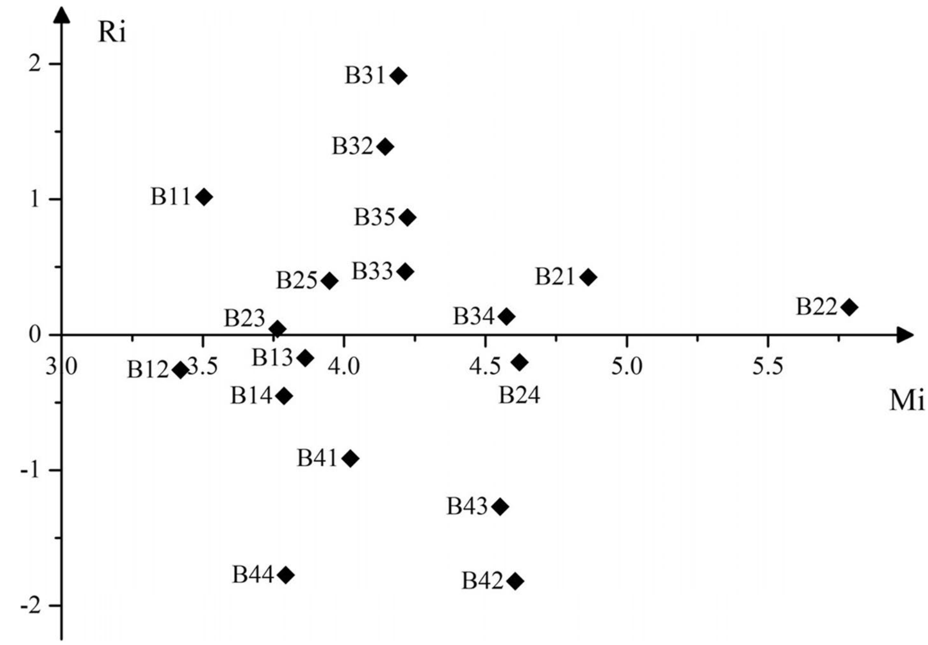

Fig. 5 Distribution of reasons and results of influencing factors

or affected relationship between these two factors and other factors in the system, and there is no reachable relationship. From the comprehensive influence matrix T, it can be seen that the degree of influence and the degree of influence of experimental equipment and technical capability B12 and corporate social responsibility B23 are also very low, indicating that the interaction between these two factors on other factors is also weak. Therefore, in the subsequent analysis, we choose to remove the isolated factors B12 and B23 for more systematic research.

Loop analysis

Against the topological hierarchical structure model diagram, if a closed-loop link of bidirectional line segments is formed, we call this link a loop, and each factor in the loop has a causal relationship with each other. From Figs. 3 and 4, we can see that there is a loop composed of four factors in the influencing factor system of artificial intelligence multi-cloud scheduling applied talent training, namely, talent management and development system B21, applied talent training investment cost B22, degree of participation in industry-university-research education B24, and strength of industry R&D and innovation support B34. These four factors have mutual causality and a strong connection within the loop. Therefore, the loop can be regarded as a subsystem of the system.

Hierarchy and causal analysis

It can be seen from the UP-type and DOWN-type topological hierarchical structure model diagrams that the influencing factor system of artificial intelligence multi-cloud scheduling applied talent training is a hierarchical structural model with four levels from the bottom to the top. The system can be divided into three levels: substantial level, extended level and superficial level.

The factor of the substantial cause level, that is, the factor located at the lowest level in the topological hierarchy model diagram, is the level factor that will only send upward directed line segments to other level factors with the strongest influence attribute and can directly or indirectly affect the factors of other strata more or less but will not be affected by other level factors, such as the root factor of the system. The factors of the substantial cause level include the professional degree of teacher structure B11, training promotion and incentive mechanism B25, Supportive Policy and Strategic Impact B31, special fund reward and subsidy standard B32 and the proportion of industrial investment in GDP B35. According to the topological map, it is not difficult to see that if we want to develop or improve the applied talent training in the artificial intelligence industry, the social factors at the root play a leading role, and the supporting policies, capital investment and subsidies of the industry have a substantial impact on other factors in the system. Second, the professional degree of teachers' structure at the college level directly affects the quality of talent training, so we should pay attention to the professional degree of teachers in the artificial intelligence industry. The promotion and incentive mechanism at the enterprise level plays a favorable role in promoting the talent quality. A complete promotion and incentive system can bring a more effective incentive effect.

The factors of the superficial level can also be called the result factors, that is, the factors located at the top level in the topological hierarchy model diagram. This level factor can only receive directed segments from other level factors but does not send directed segments to other level factors, which is the most affected. The superficial factors are as follows: practical training base construction and education integration degree B13, professional re-education intensity B14, career goals height B42, innovative self-efficacy B43, and awareness of industry and corporate standards B44. This paper analyzes the factors of superficial level, which only involves the factors of individual level and college level, indicating that it has a more direct impact on the results of talent training. At the individual level, the talent's career goal height, self-efficacy and cognition of the industry are more affected by the factors at the enterprise level and social level. Therefore, to improve the impact of this level factor on the system, the breakthrough lies in the regulation of the corresponding influencing factors at the enterprise level and social level. At the college level, the integration of the training base and education and the intensity of professional reeducation can directly affect the professional quality and practicability of talent, but these two factors are inseparable from enterprise-related factors.

The factor of the extended level, meaning the factor located in the middle part of the topological hierarchy model diagram, sends upward-directed segments to the upper-level factors to affect the upper-level factors. At the same time, it also receives the directed line segments from the lower-level factors, so the factors have strong extensional influence and the degree of influence. The factors that extend the level include talent management and development system B21, applied talent training investment cost B22, degree of participation in industry-university-research education B24, industry R&D and innovation support B34, individual characteristics B41, artificial intelligence major and school evaluation B33. By analyzing the factors at this level, the factors at the enterprise level have a stronger centrality degree. Therefore, the enterprise's talent management and development system, the investment cost of relevant talent and the degree of participation in training have a strong control force on the development or promotion of applied talent in the artificial intelligence industry. These three factors are also mutually causal; consequently, when taking measures, we can focus on one of them. Then, the evaluation of artificial intelligence majors and related schools at the social level and the support for enterprise R&D and innovation have a considerable positive incentive effect on talent. The individual characteristics at the individual level generally refer to the personality and knowledge of talent, which has a key impact on talent training.

Summary and suggestions

Based on the calculation and result analysis in the third and fourth chapters, this paper puts forward targeted countermeasures and suggestions for the training of artificial intelligence multi-cloud scheduling applied talent. The targeted development suggestions are as follows:

Increasing industrial investment and subsidies to boost the development and construction of the artificial intelligence industry

The supportive policies, capital investment and subsidies of the artificial intelligence industry are the key factors affecting the development of the artificial intelligence industry and are of decisive importance to the future development direction of the industry. Supportive policies for industrial development are the most favorable measures to encourage enterprises, colleges and individuals to focus more on the artificial intelligence industry. The increase in industrial capital investment can drive the layout of enterprises in the artificial intelligence industry and expand the scale of construction. Targeted and refined subsidy policies can encourage enterprises to increase investment in related projects and technology research and development and effectively reduce the pressure on enterprises in terms of industrial development funds. The continuous exploration and development of enterprises in the artificial intelligence industry will inevitably increase the demand for high-quality applied talent in the artificial intelligence industry, thereby continuously promoting the optimization of the applied talent training system.

Enabling enterprises expand the layout of talent related to IoT multi-cloud scheduling to meet the needs of enterprises for refined talent

Corporate social responsibility is the most original factor in the system, while the enterprise's investment cost in the training of multi-cloud scheduling applied talent and the talent management and development system are the two most central factors in the system. These three factors are all subordinate to the enterprise level. From this perspective, the expansion of the layout and investment of enabling enterprises in IoT multi-cloud scheduling talent is the basis for the cultivation of multi-cloud scheduling applied talent. Enterprises with a high sense of social responsibility have a high vision of supporting the development of the artificial intelligence industry and have a subtle influence on the cultivation of the professional quality of cloud scheduling-related talent in the training process. In addition, enterprises that invest a high cost in talent related to multi-cloud scheduling and have a relatively complete talent management and development system not only have a stronger attraction for talent but also play a crucial role in improving the systematization of applied talent training related to multi-cloud scheduling.

Strengthening the construction of the professionalism of the faculty structure and establish a high-quality and high-standard training team

The professional degree of the faculty structure belongs to the class of substantive causes, which is the most direct factor affecting the training results of artificial intelligence multi-cloud scheduling applied talent. Moreover, teachers should have diversified theoretical knowledge and practical literacy in the field of artificial intelligence and multi-cloud computing resource scheduling. The professional level of teachers' teaching contents and methods directly affects the quality and level of applied talent education and training. Therefore, it is necessary to strengthen the teachers' knowledge and skills in related fields based on artificial intelligence, big data, cloud computing platforms and technologies. The training syllabus and goals for multi-cloud scheduling applied talent should be more targeted and systematic so that the teaching content can keep up with the pace of the times and adapt to the development of the industry. We can also improve and develop curriculum resources through internal and external cooperation and drawing lessons from foreign curriculum systems. At the same time, the professional faculty structure of the university also creates favorable conditions for cooperation between the industry, the university and the research institute, and the high quality and high standard training team also boosts the training process of multi-cloud scheduling applied talent.

Strengthening the development mind of multi-cloud scheduling-related talent and improving the subjective initiative of talent training

Highly industrious talent career goals are one of the factors of the system centrality degree being higher, which has a strong influence on the system. The characteristics of the talent themselves determine their subjective initiative and self-efficacy in the training process to a certain extent. Talent with higher career development goals will show higher pursuit and development vision in the training process. However, people cannot establish their career development goals and development directions from the beginning. Therefore, in talent training, we should strengthen the recognition of talent for the artificial intelligence industry, the IoT and multi-cloud computing, strengthen the development mind of artificial intelligence multi-cloud scheduling applied talent, strengthen the guidance of their career development goals and plans, guide them to form the career values of highly skilled talent, and enhance their initiative and enthusiasm in the training process to promote the training of applied talent for multi-cloud scheduling.

Conclusion and future work

Based on the research background of multi-cloud scheduling supported by artificial intelligence, this paper constructs the influencing factor model of multi-cloud scheduling applied talent training of artificial intelligence. Based on the DEMATEL method and the improved AISM method, it further measures the influence path and hierarchical distribution in the system of the training quality of multi-cloud scheduling applied talent driven by various factors. Thus, the driving structure and action mechanism of the internal influencing factors of the system are revealed, and the current situation is analyzed, Finally, some measures and suggestions are put forward.

However, when using the DEMATEL method to build the original matrix, due to the limitations of questionnaire surveys and expert scoring, the research experts in this paper focus on the fields of artificial intelligence and the Internet of Things and rely on subjective feelings to have a greater impact. Therefore, the results and analysis are more suitable for the reference of the research fields related to artificial intelligence cloud scheduling applied talent. In the future, in addition to expanding the volume of the questionnaire, fuzzy theory can be introduced to eliminate the subjectivity of expert scoring and provide more powerful support for identifying key influencing factors.

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Authors' contributions

Conceptualization was performed by Yi-jie Bian; investigation was conducted by Jing-qi Li and Lu Xie; methodology was performed by Yi-jie Bian and Lu Xie; writing of the original draft was performed by Lu Xie; and review and editing was carried out by Yi-jie Bian and Jing-qi Li. The author(s) read and approved the final manuscript.

Authors' information

Yi-jie Bian was born in 1964. He received a Ph.D. degree in Technical Economics and Management from Hohai University, Nanjing. He is currently a professor in the Department of Management Science and Information Management, Business School, Hohai University. His research interests include information management and educational informatization.

Lu Xie received a bachelor's degree in E-commerce from Henan University in 2015. She is currently pursuing a master's degree in Management Science and Engineering, Hohai University. Her research interests are on information management and educational informatization.
Jing-qi Li is a senior engineer of Network Security and Information Management Office of Hohai University. He is currently a Ph.D. candidate in Management Science and Engineering, Hohai University. His research interests focus on big data analysis and artificial intelligence.

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

Declarations

Ethics approval and consent to participate
Not applicable.

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The authors declare that they have no competing interests.

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