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Article

Research on the training model of vocational education under the interface between technological progress and the housing industry

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Abstract: The new round of scientific and technological revolution and industrial change are profoundly reshaping the global economic landscape, and cutting-edge technologies such as artificial intelligence, big data, and Internet of Things are accelerating the penetration of traditional industries. The housing industry, as an important pillar of the national economy, is experiencing a critical period of transformation from traditional construction methods to intelligent, green and industrialized. In order to explore the optimization path of vocational education training mode under the interface of scientific and technological progress and housing industry, this study carries out a systematic analysis of the influencing factors of talent training based on the DEMATEL-ISM-MICMAC model and Bayesian network evaluation model. The study constructed an evaluation system containing a total of 15 influencing factors at three levels of multi-faceted policy, multi-dimensional environment and multi-dimensional innovation, and obtained data and conducted empirical analysis through expert survey method. The results show that: the centrality of participation in innovation enthusiasm, scientific research and innovation ability, and local government expenditure on vocational education rank in the top three respectively, of which the centrality of participation in innovation enthusiasm reaches 16.752; 55% of the probability of input-output performance of vocational education training mode is at a high level, and 58% of the probability of talent cultivation level is at a high level; the sensitivity analysis reveals that the sensitivity of researchers' full-time equivalence is the highest up to 15.45; Bayesian network analysis found that the probability of the growth rate of talent cultivation output can reach 0.585 when the growth level of school dormitory area is high. The study provides theoretical support and practical guidance for constructing a vocational education cultivation model adapted to the needs of scientific and technological progress and the development of the housing industry.

Keywords: Vocational education training model; DEMATEL-ISM-MICMAC model; Bayesian network; influencing factors; scientific and technological progress; housing industry

1. Introduction

With the continuous progress and innovation of science and technology, its interface with the housing industry has gradually deepened, prompting continuous change and development in the housing field [1-2]. Science and technology innovation plays an important role in promoting the future development of housing, which not only improves the quality and comfort of housing, but also brings more convenience and intelligent experience for people's life [3-5]. It is mainly embodied in the following aspects, (i) smart home: With the continuous development of Internet of Things (IoT) technology, smart home is more and more favored by consumers [6]. Now, we can control the lights, temperature, security and so on at home through smart phones or voice assistants, which not only improves the comfort of the housing, but also improves the security of the housing [7-9]. (ii) Green building: with the increasing awareness of environmental protection, more and more people are focusing on the environmental friendliness of housing [10]. Green building reduces the impact of housing on the environment through the use of renewable energy, energy-saving equipment, environmentally friendly materials, etc., and also improves the comfort and health of housing [11-12]. (iii) 3D printing technology: the application of 3D printing technology makes the construction of housing faster and more accurate [13]. Through 3D printing technology, it can reduce the waste in the construction process, and it can also achieve personalization to meet the different needs of consumers [14-15].

However, the connection between science and technology and housing is inseparable from the support of professionals, which requires vocational education to appropriately reform the talent training model according to market demand, and only by continuously absorbing new technologies and innovating teaching models can vocational education provide students with better learning experience and employment services, so as to cultivate excellent scientific and technological talents and provide support for "science and technology housing" [16-19].

This study adopts the DEMATEL-ISM-MICMAC integrated model and the Bayesian network evaluation method to systematically analyze the influencing factor system of vocational education talent cultivation, construct a multilevel recursive structural model, and identify the key constraints and driving factors. Through the establishment of Bayesian network evaluation model, the input-output performance of vocational education training mode is quantitatively evaluated, revealing the causal relationship and mechanism of action between the influencing factors. The study provides a scientific basis for constructing a vocational education training model that adapts to the needs of scientific and technological progress and the development of the housing industry, and serves as a reference for governmental departments to formulate relevant policies and for colleges and universities to optimize their talent training programs.

2. Analysis of factors affecting the training of vocational education personnel

In order to explore the vocational education training model under the interface of technological progress and the housing industry, this chapter analyzes the influencing factors of talent development using the DEMATEL-ISM-MICMAC model.

2.1. Principles of the DEMATEL-ISM model

DEMATEL-ISM model is the product of the integration of Decision Making Experiment and Evaluation Test Method (DEMATEL) [20] and Interpretive Structural Model (ISM) [21], in which the DEMATEL method is suitable for analyzing the distribution of influencing factors influence degree, influenced degree, center degree and cause degree. However, the disadvantage of DEMATEL is that it cannot intuitively express the hierarchical structure relationship between the influencing factors, in order to make up for the shortcomings of the DEMATEL method, this paper further introduces the ISM method, which can intuitively and concretely present the direct influence relationship between the influencing factors of the complex system through the establishment of the influencing factor hierarchical analysis diagram. Among them, the algorithm of DEMATEL-ISM is in the following relationship, the calculation of DEMATEL model is carried out first, and then further hierarchical calculation and analysis is carried out on the basis of the calculation results by using ISM method.

2.2. Principles and steps of DEMATEL method and ISM modeling

2.2.1. Principle of the DEMATEL method

The DEMATEL method is a commonly used method for analyzing system factors and is based on the principles of graph theory and matrix theory. The method analyzes the logic of interconnections between the elements of the system by constructing a direct influence matrix, and then calculates the degree of influence and the degree of being influenced by each influencing factor. In addition, the attributes of each factor can be determined according to the center degree and cause degree indicators, and the structural diagram of the whole system can be adjusted according to these indicators to make the system structure more rational.

2.2.2. Steps of the DEMATEL method

(1) Establishment of direct influence matrix

In this paper, the expert survey method and Likert five-point scale method are used to assess the intensity of influence between factors, and the degree of influence is categorized from weak to strong into 0, 1, 2, 3 and 4 points, which means: no influence, weak influence, average influence, strong influence, and very strong influence, respectively. After integrating and processing the data, the direct impact matrix was constructed X :

$$X = \begin{bmatrix} 0 & x_{12} & \cdots & x_{1n} \\ x_{21} & 0 & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & 0 \end{bmatrix} \tag{1}$$

(2) Establishment of normative direct impact matrix

In order to normalize the direct influence matrix X , this paper adopts the row maximum method, summing each row of the matrix X , taking the maximum value of it, and dividing all the elements in the matrix X by the maximum value to obtain the canonical influence matrix N :

$$N = \frac{X_{ij}}{Max\left(\sum_{j=1}^{n} x_{ij}\right)} \tag{2}$$

(3) Constructing the integrated impact matrix

Operate on the normative direct impact matrix N to construct the integrated impact matrix T . The calculation formula is as follows:

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

(4) Calculation of the degree of influence, degree of being influenced, degree of centrality and degree of cause of factors

The degree of influence refers to the sum of the rows in the matrix T , which represents the combined influence value of the elements in each row on all other elements, and is denoted as D_i :

$$D_i = \sum_{j=1}^{n} x_{ij} (i = 1, 2, \ldots, n) \tag{4}$$

The degree of being influenced refers to the sum of the columns in the matrix T , which represents the value of the combined influence of the elements in each column on all other elements, denoted as C_i :

$$C_i = \sum_{j=1}^{n} x_{ij} (i = 1, 2, \ldots, n) \tag{5}$$

The centrality indicates the position of the factor in the evaluation system and the size of the role it plays, and the centrality of a factor is the sum of its influencing and influenced degrees, denoted as M_i :

$$M_i = D_i + C_i \tag{6}$$

The degree of cause is obtained by subtracting the degree of influence and the degree of being influenced by an element and is denoted as R_i :

$$R_i = D_i - C_i \tag{7}$$

2.2.3. Principles of ISM modeling

The Interpretative Structural Modeling (ISM) method is a model designed to analyze the problems of complex socio-economic systems. The method is characterized by the decomposition of complex systems into a number of subsystems and the use of electronic computer technology, which ultimately builds the system into a multilevel structural model. This method helps to understand and analyze the inner relations and operational mechanisms of complex systems in greater depth. It can be seen that the explanatory structural model method can further analyze the system in depth, decompose the complex system into a number of subsystems for study, and further analyze the direct binary relationship between these subsystems, and decompose the whole system structure into a hierarchical analytical diagram, i.e., a topological diagram.

2.2.4. Steps in ISM modeling

(1) Introduction of threshold value λ

Based on the revised values in the integrated impact matrix T in the DEMATEL model, the threshold value λ is determined and introduced, and the redundant numerical information in the integrated impact matrix T can be eliminated through λ to get the adjacency matrix A which consists of 0 and 1 only, and the specific formula of the threshold value λ is as follows:

$$\lambda = \alpha + \beta \tag{8}$$

Where α is the average of the values in the integrated impact matrix T and is the standard deviation of the values in the integrated impact matrix T.

(2) Establishment of Neighborhood Matrix A

The values in the composite influence matrix T are filtered, where values greater than or equal to λ are taken as 1, and values less than λ are taken as 0. The adjacency matrix $A = [a_{ij}]_{n \times n}$ can be obtained, where $a_{ij} = 0$ or 1, and 0 means that the factor X_i has no direct effect on the factor X_j, and 1 means that the factor X_i has a direct effect on the factor X_j, which is given by the following formula:

$$\begin{cases} t_{ij} \geq \lambda (i, j = 1, 2, 3, ..., n) a_{ij} = 1 \\ t_{ij} < \lambda (i, j = 1, 2, 3, ..., n) a_{ij} = 0 \end{cases} \tag{9}$$

Where t_{ij} represents the value of column j in row i in the combined influence matrix T, and a_{ij} represents the value of column j in row i in the adjacency matrix A.

(3) Create multiplication matrix B

The multiplication matrix B is obtained by adding the adjacency matrix A and the unit matrix I, which is given by:

$$B = A + I \tag{10}$$

(4) Create a reachable matrix R.

Repeatedly self-multiply the multiplication matrix B until the result of the operation no longer changes, at this point you can get the reachable matrix R.

(5) Determine the hierarchical relationship

Hierarchical processing of the reachable matrix R, you can determine the reachable set R, antecedent set Q intersection C of each influence factor.

Reachable set R: the set of column elements corresponding to matrix elements containing 1 in the rows corresponding to elements a_{ij} in the reachable matrix R, which represents the elements that will be reached by a_{ij}.

Antecedent set Q: the set of row elements corresponding to matrix elements containing 1 in the columns corresponding to the elements a_{ij} of the reachable matrix R, which denotes the other elements that reach the element a_{ij}.

Intersection C: the intersection of the reachable set with the prior set, i.e., $C_i = R_i \cap Q_i$.

If $R_i = C_i$ holds, the element and its corresponding row and column are removed from the whole and this step is repeated continuously until the hierarchy of influence of all the elements is clarified, resulting in the final hierarchical analytic map.

2.3. MICMAC model construction

The MICMAC model [22] can be realized to complement and extend the above DEMATEL-ISM analysis. Based on the ISM reachability matrix U, the dependency and driving force values calculated according to Eqs. (11) to (12), the dependency-driving force diagram is drawn to clarify the position and role of the influencing factors in the system:

$$Q_i = \sum_{j=1}^{17} u_{ij} (i, j = 1, 2, \boxed{?}, 17) \tag{11}$$

$$Y_i = \sum_{i=1}^{17} u_{ij} (i, j = 1, 2, \boxed{?}, 17) \tag{12}$$

2.4. Empirical study and analysis of results

DIM model, i.e. DEMATEL-ISM-MICMAC model, is a new type of system analysis method in which the three methods of DEMATEL method, ISM model and MICMAC method are linked. The study aims to realize three research objectives: first, to systematically sort out the key influencing factors in the process of vocational education talent cultivation, and to provide a powerful grip for vocational education talent cultivation. The second is to clarify the hierarchical relationship between each factor, which will help the government and colleges and universities to make precise policies. Thirdly, it clarifies the substantive role of each factor in the vocational education talent cultivation system and provides new ideas for enhancing the effect of vocational education talent cultivation. The analysis of influencing factors of vocational education talent cultivation under the docking of scientific and technological progress and housing enterprises is a complex systematic problem, and DIM model is applicable.

2.4.1. Construction of a system of influencing factors

Establishing a scientific, comprehensive and intuitive evaluation system is a key step in building the model. The selection of influencing factor indicators should follow the principles of systematicity, scientificity, completeness and operability. By combing the existing literature and discussing with professionals and providing feedback, this study has refined and summarized a total of 15 influencing factor indicators of vocational education talent cultivation in three levels, including multi-faceted policy, multi-environment, and multi-dimensional innovation, as shown in Table 1.

Table 1. The index system of influencing factors for talent cultivation in vocational education

Target layer	Criterion layer	Index layer	Index number
Influencing factors of talent cultivation in vocational education (A)	Multi-faceted policy (A_1)	Local government expenditure on vocational education	A_{11}
		Policy support for talent introduction	A_{12}
		Entrepreneurship incentive policy support	A_{13}
		Policy support for vocational education talents	A_{14}
		The guiding effect of ideological and political spirit	A_{15}
	Diverse environment (A_2)	Market environment	A_{21}
		Social environment	A_{22}
		Financing environment	A_{23}
		Service environment	A_{24}
		Cultural environment	A_{25}
	Multi-dimensional innovation (A_3)	Degree of teaching innovation	A_{31}
		Curriculum innovation level	A_{32}
		Enthusiasm for participating in innovation	A_{33}
		Scientific research and innovation ability	A_{34}
		Innovative competition achievements	A_{35}

This study utilized the Delphi method to conduct the research, formed 15 indicators into a 15×15 matrix, and invited 10 experts to rate the importance and relevance of the evaluation indicators of vocational education talent cultivation by using the 0-5 scale method, and the invited experts were high-level and high-precision talents in the field of vocational education. The scoring results were analyzed for reliability using the SPSSAU platform, and the reliability coefficient was 0.954>0.9, indicating that the research data were of high quality in terms of reliability, and the scoring results were applicable to subsequent research.

2.4.2. DIM Model Analysis

(1) Importance analysis of influencing factors

The DEMATEL method was used to quantitatively analyze the 15 influencing factors, solving for the degree of influence D, the degree of being influenced C, the degree of centrality M, and the degree of cause R. Considering the complexity of the calculation, this study used Python 3.13.1 software to carry out the operation, and the DEMATEL results were obtained after the unified collation as shown in Table 2.

The top three factors in terms of centrality are participation in innovation enthusiasm (A33), scientific research and innovation ability (A34), and local government expenditure on vocational education (A11), indicating that these three factors are the most important for vocational education talent cultivation, and are ranked at the top of the list in terms of influenced degree, and need to be regarded as key constraints to be controlled and managed. The centrality of each influencing factor in the policy factor is at a high level and close to each other, indicating that the policy factor has a high status in the influencing factor system of vocational education talent cultivation, and that relevant policies and ideological education methods must be reasonably formulated to promote the high-quality cultivation of vocational education talents.

Table 2. DEMATEL results

Factor	D	Ranking	C	Ranking	M	Ranking	R	Ranking	Factor type
A_{11}	8.334	2	7.927	5	16.261	3	0.407	5	Reason factor
A_{12}	7.916	6	8.221	3	16.137	4	-0.305	9	Result factor
A_{13}	8.223	3	7.192	9	15.415	8	1.031	2	Reason factor
A_{14}	8.052	4	7.385	10	15.437	7	0.667	3	Reason factor
A_{15}	8.419	1	6.158	15	14.577	9	2.261	1	Reason factor
A_{21}	7.991	5	7.596	6	15.587	6	0.395	6	Reason factor
A_{22}	7.504	9	6.899	11	14.403	12	0.605	4	Reason factor
A_{23}	7.127	11	6.821	12	13.948	13	0.306	7	Reason factor
A_{24}	6.147	14	6.195	14	12.342	14	-0.048	8	Result factor
A_{25}	7.008	12	7.564	7	14.572	10	-0.556	11	Result factor
A_{31}	6.963	13	7.456	8	14.419	11	-0.493	10	Result factor
A_{32}	5.722	15	6.369	13	12.091	15	-0.647	13	Result factor
A_{33}	7.899	7	8.853	2	16.752	1	-0.954	14	Result factor
A_{34}	7.186	10	9.209	1	16.395	2	-2.023	15	Result factor
A_{35}	7.526	8	8.137	4	15.663	5	-0.611	12	Result factor

(2) Hierarchical relationship analysis of influencing factors

The overall influence matrix obtained from the DEMATEL method is repeatedly calculated and tested to determine the threshold $\lambda=0.52$, and is calculated using Python 3.13.1 to obtain the reachable matrix, and then the multilevel recursive order structure model of the influencing factors of vocational education personnel training is drawn according to the ISM calculation method as shown in Figure 1. Each influencing factor is characterized by multilevel recursive order, which is divided into five levels from bottom to top.

According to the results of ISM and DEMATEL model, the influencing factors are divided into three categories: surface, middle and deep. First, the surface level factors, which are located in level 1 of the multilevel recursive structural model, such as participation in innovation motivation (A_{33}), scientific research and innovation ability (A_{34}), and innovation competition results (A_{35}) can play a direct and rapid role in vocational education talent cultivation. Combined with Table 2, it can be seen that the centrality of participation in innovation enthusiasm (A_{33}) and scientific research and innovation ability (A_{34}) ranks in the top two, which indicates that these two factors have a strong comprehensive correlation with other factors and are very easy to be influenced. Combined with Figure 1, it can be seen that the policy support for talent introduction (A_{12}), cultural environment (A_{25}), and the degree of teaching innovation (A_{31}) mainly influence vocational education talent cultivation indirectly through the participation in innovation enthusiasm (A_{33}) and scientific research and innovation ability (A_{34}). The innovative competition results (A_{35}) show a strong passivity, the index value of influence ranks relatively low, and the comprehensive correlation embodied in the center degree is not obvious, so the degree of importance of the innovative competition results (A_{35}) in the system is not high.

The second category is the middle level factors, located in the 2nd, 3rd and 4th levels, local government vocational education expenditure (A_{11}), talent introduction policy support (A_{12}), entrepreneurship incentive policy support (A_{13}), vocational education talent policy support (A_{14}), market environment (A_{21}), social environment (A_{22}), financing environment (A_{23}), cultural environment (A_{25}), the degree of pedagogical innovation (A_{31}) constitute the transitional elements of vocational education talent cultivation. As can be seen through Table 2, the centrality of local government vocational education expenditure (A_{11}) and talent introduction policy support (A_{12}) ranked third and fourth, respectively, and the degree of being influenced ranked in the first two of the middle tier factors, with the degree of influence in the middle and upper levels, indicating that these two types of factors have a strong correlation for the upper and lower tiers, and they should be paid attention to during the process of vocational education talent cultivation. The centrality value of entrepreneurship incentive policy support (A_{13}), policy support for top talents (A_{14}), and market environment (A_{21}) is not high, and the cause index is positive, and the influence index value is very high, which has an important influence and promotion effect on other factors. The centrality of social environment (A_{22}) is low, in the middle level of the cause factors, and has a certain influence on other factors but the influence is small. The cultural environment (A_{25}) has a low degree of centrality and influence, indicating a small role in the whole system. The cause degree value of financing environment (A_{23}) is in the penultimate place in the cause factor group, and its cause degree index value is only 0.306, and the cause degree value of the degree of teaching innovation (A_{31}) is -0.493, which shows a weak passivity, but its influence degree value and centrality value are not high, indicating that the degree of teaching innovation (A_{31}) and the financing environment (A_{23}) have a small role in the system of influencing factors.

The third category is the underlying factors, and the effect of Civic and Political Spiritual Guidance (A_{15}), the service environment (A_{24}), and the level of curricular innovation (A_{32}) constitute the root factors of the influencing factor system, which have a profound and sustained impact on the cultivation of vocational education talents. The service environment (A_{24}) and the level of curriculum innovation (A_{32}) have cause degree values of -0.048 and -0.647, and these two types of factors have low correlation and low degree of influence, and play a small role in the system. The effect of Civic and Political Spiritual Guidance (A_{15}) ranks first in the cause degree value, ranks medium in the center degree, and ranks first in the influence degree value, indicating that the effect of Civic and Political Spiritual Guidance will have a strong influence on other factors.

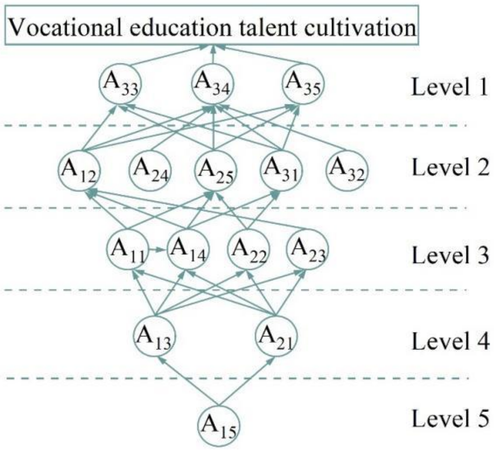

Figure 1. Multi-level hierarchical interpretation structure model

(3) Driving force-dependence matrix analysis of influencing factors

After calculating the driving force and degree of dependence of each influencing factor according to Table 2, Matlab was used to draw the influencing factor driving force - degree of dependence matrix diagram, driving force indicates the degree of influence on other factors, and degree of dependence indicates the degree of influence by other factors. The average value of drive and dependency is used as the dividing line and finally divided into 4 quadrants, the drive-dependency matrix based on MICMAC model is shown in Figure 2.

According to the results of the MICMAC model, Region I belongs to the autonomous factors with low driving force and low dependence, and the factors of financing environment (A_{23}), service environment (A_{24}), and the level of curricular innovation (A_{32}) have small correlation and influence, which are not easy to trigger the chain effect, and are not easily affected by the factors of other regions in the system. Region II belongs to the driving factors with high driving force and low dependence, and the policy support of vocational education talents (A_{14}), the effect of the guidance of the spirit of civics (A_{15}), and the social environment (A_{22}) are easy to influence other factors in the whole system. These three factors rank high in the cause factors and are located at the lowest level in the ISM, driving the other levels, which are the deep core factors driving vocational education talent development. Region III is a high driving force and high dependence correlation factor, the market environment (A_{21}), innovative competition results (A_{35}), local government vocational education expenditure (A_{11}) and other factors in this region are vulnerable to other factors while maintaining a high driving force, which is a risky factor, and it is necessary to take careful consideration when applying policies to such factors in vocational education personnel training to avoid a chain effect. Region IV belongs to the dependency factors with low driving force and high degree of dependency, cultural environment (A_{25}), degree of teaching innovation (A_{31}), scientific research and innovation ability (A_{34}) are located in the high level in ISM, which are susceptible to the influence of other factors in the system, and will have a direct impact on the cultivation of vocational education personnel, which is an aspect that needs to be emphasized in the process of cultivation.

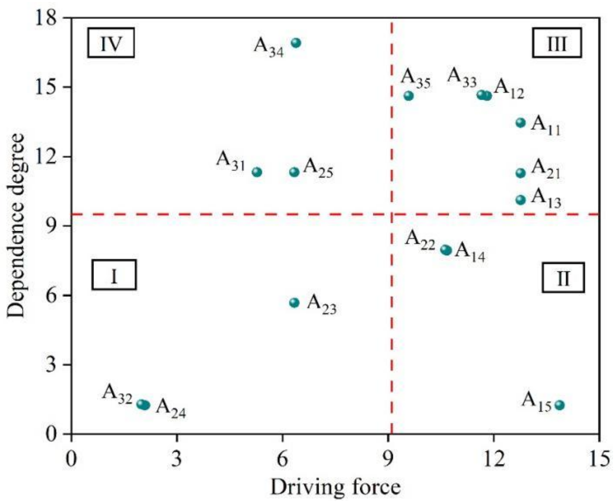

Figure 2. Driving force-dependency matrix

3. Bayesian network evaluation model construction of vocational education training mode

Based on analyzing the influencing factors of vocational education talent cultivation, this chapter uses Bayesian network to evaluate the input-output performance of related vocational education cultivation modes.

3.1. Principles and modeling of Bayesian network approach

3.1.1. Principles of the Bayesian network approach

Bayesian networks (BN) are graphical network models describing uncertain causal relationships between indicator variables and are used for modeling and reasoning about uncertain systems. Bayes' theorem utilizes a priori knowledge of the occurrence of an event in conjunction with evidence of new changes in the event and uses changes in the evidence of the event to infer the direction and circumstances of the event's development and change, from which Bayes' theorem can be obtained as a Bayesian formula:

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A)} \tag{13}$$

Where: $P(A), P(B)$ is the a priori probability, refers to the size of the possibility of the occurrence of the event A, B identified based on objective experience, existing information, objective knowledge, expert judgment and so on. A priori probability is the estimation of the occurrence of the event before the experiment, it is a kind of estimated probability, which can be obtained through subjective estimation, or objective probability can be obtained based on historical information. $P(A \mid B)$ denotes the conditional probability, which refers to the magnitude of the likelihood that event A will occur under the precondition of event B. $P(B \mid A)$ is the a posteriori probability, which refers to the probability of event A occurring according to the new conditions, so as to get the size of the likelihood of event B occurring.

Bayesian network combines probability theory and graph theory, the nodes in the network graph can also be called node variables, representing the Bayes theorem of the probability of the occurrence of the event and the state in which it is located, connecting arcs indicate whether the two nodes are interacting with each other or not, and if there is no connecting line between the two nodes, it means that the conditions between these two nodes are independent.

Thus the Bayesian network can be represented as $N = (G, I)$, where:

(1) G is the Bayesian network structure, consisting of variable nodes and arcs, assuming that $G = \{AI, A2, ..., An, B\}$, A_i are the nodes and B denotes the set of all directed arcs.

(2) I denotes the set of Bayesian network node probabilities, which is assumed to be

$\{A_l, A_2, ..., A_n\}$, when $A_l, A_2, ..., A_n$ are independent of each other, we have by the chain rule:

$$P = (A_1, \quad A_2, \ldots, \quad A_n) = \prod_{i=1}^{n} P(A_i \mid P_a(A_i)) \tag{14}$$

Let the prior probability be $P(A_i)$, and the new information obtained after statistical processing through the questionnaire be $P(B \mid Ai)$, where the posterior probability is when $i = 1, 2, \boxed{?}, n$:

$$P(A_i / B) = \frac{P(B / A_i) \cdot P(A_i)}{\sum_{i=1}^{B} P(B / A_i) \cdot P(A_i)} \tag{15}$$

3.1.2. Bayesian network modeling

The process of Bayesian network modeling is shown in Figure 3, which is mainly divided into the following five steps:

(1) Problem definition and formulation: before constructing a model, first determine the problem to be studied, and reserve relevant knowledge in advance before constructing a Bayesian network model to ensure the reasonableness of the constructed network model as well as the correctness of the a priori probability.

(2) Determine the set of variables and the domain of variables: when constructing a Bayesian network model, it is necessary to select appropriate nodes, and the evaluation accuracy will be reduced when there are fewer node variables. However, when there are more nodes, it will make the construction of the Bayesian network more difficult, and at the same time, it may reduce the accuracy of the evaluation results of the model and the speed of operation, therefore, it is necessary to use a suitable method to screen the variables.

(3) Determine the structure of the Bayesian network: at present, there are often three methods to determine the structure of the network, one method is to collect the complete data of the problem to be researched, and through the function of parameter learning of the Bayesian network, the variables are sorted to determine the conditional independence between the variables. The second method is to build the network structure based on empirical knowledge and sample data. The third method is to define the variables by using the expert evaluation scoring method with experts as the dominant.

(4) Determine the conditional probability table of nodes: the basis of Bayesian network is to obtain the prior probability of the root node and the conditional probability of the cause node in the Bayesian network. In this paper, we combine statistical data with expert knowledge and use the triangular fuzzy number method to process the node variables and obtain the conditional probability of each node variable, including the processing of singular values, missing values and the discretization of data.

(5) Actual network construction: after the completion of the preliminary work, the existing data and algorithmic models are used to construct the Bayesian network model, and examples are verified after the completion of the initial model construction to verify the scientific validity of the Bayesian network model. If there are problems, the model can also be amended so that the model meets the needs of evaluation precision and accuracy.

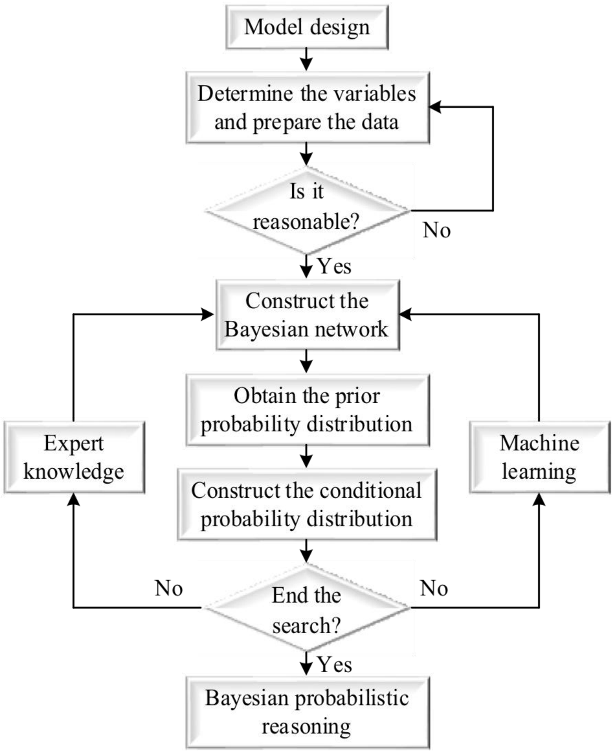

Figure 3. General steps of Bayesian network modeling

3.2. Constructing Bayesian networks based on causality

This paper adopts the causality method to construct a Bayesian network using the interrelationships between the variables, so as to realize the evaluation of the input-output performance of the vocational education training model.

3.2.1. Process of constructing Bayesian networks based on causality

Vocational education personnel training is a long-term, complex process, so the corresponding Bayesian network constructed will have many node variables. At the same time, there is a sequential relationship between the variable nodes, and different sequential relationships make the final construction of the Bayesian network model is completely different, and the results obtained are also very different, so it is necessary to strictly consider the comprehensive influence relationship between the risk factors in the process of vocational education personnel training. There are two main methods for constructing Bayesian networks: the variable ordering method and the causal relationship method. Considering that a part of the factors in the process of vocational education personnel training cannot be objectively quantified by data, this paper adopts the causal relationship method, which utilizes the interrelationships between variables to construct the Bayesian network.

When constructing the Bayesian network model using causality, if we simply use the expert's empirical knowledge to analyze the relationship between the influencing factors of vocational education talent cultivation, it will make the constructed Bayesian network structure not accurate and rigorous enough. Considering that vocational education talent cultivation is a practical process, the questionnaire can be expanded from experts to experts and college students in the field of talent cultivation by distributing the questionnaire. The initial Bayesian network model is constructed to make solutions to specific practical problems, so the initial Bayesian network model can be constructed according to the results of the preliminary questionnaire survey, and then adjusted according to the actual situation of talent cultivation, so as to construct a Bayesian network structure model that best meets the actual situation. The specific implementation steps of Bayesian network method evaluation of vocational education training mode are shown in Figure 4.

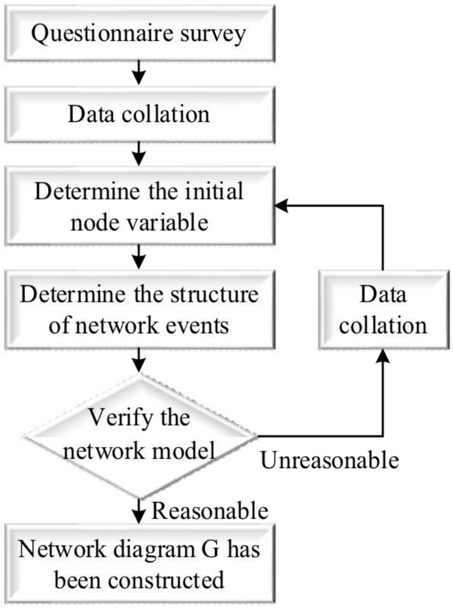

Figure 4. The process of constructing a Bayesian network

3.2.2. Deriving parameters of Bayesian networks based on causality

According to the evaluation index system of input-output performance of vocational education training mode and the causal relationship between the index factors, the Bayesian network structure diagram of the input-output performance index of vocational education training mode can be constructed, and then the questionnaire survey method and the expert evaluation method are used to obtain the Bayesian network node variables of the influencing factors. Due to the complexity of the Bayesian network calculation process, this paper uses the BNT toolbox in MATLAB to calculate the results of the constructed fuzzy Bayesian network.

According to Bayes' theorem and Bayesian network method, assuming that there are n node variables in the network model, the node variables can be expressed as $M_l, M_2, ..., M_n$, let the state value of M_i be k, and take the probability interval of M_i in the k state as $[x, y]$, and have:

$$P(M_i = k) = I[(x+y)/2] \tag{16}$$

I denotes the set of all parameters of the node variable M_i in the k state.

According to the basic theorem of Bayesian networks and the conditional independence of the node variables from each other, there are:

$$\begin{aligned} P(M_i = k) &= \sum_{M_1, M_2, \ldots, M_k, \ldots, M_n} P(M_1, M_2, \ldots M_n) \\ &= \sum_{M_1, M_2, \ldots, M_k, \ldots, M_n} P(E_i = k \prod M - k) \end{aligned} \tag{17}$$

According to the a priori probability of the parent node obtained from the Bayesian network and the questionnaire survey, the probability of the occurrence of each child node after the parent node can be introduced by the formula (17), and the probability value of the requested node variable can be obtained in the end, which is the basic principle of deducing the parameters of the Bayesian network according to the causal relationship. The BNT toolbox in Matlab software is used in the practical application, and after modeling programming and continuous correction, the Bayesian network model for input-output performance evaluation of vocational education training model is finally constructed, which can accurately evaluate the performance of vocational education training model.

3.3. Empirical analysis

3.3.1. Processing and analysis of data

(1) Data collection and discretization

The research object of this chapter is the input and output performance evaluation of vocational and other education training model in Province H. That is to say, through the input and output indicators of vocational education training model in Province H, we analyze the correlation between the input indicators and the output indicators, and then find the most sensitive factors affecting the final performance evaluation, so as to provide reference for the further improvement of the model. This paper is selected from the data of 2012-2022, due to the availability of data and the research method can be operated specifically, to determine the input indicators and output indicators after the finalization and merger of the final selection of a total of 14 indicators to build a Bayesian network, and the rate of change of the indicators to be expressed specifically. Bayesian network model to deal with discrete variables better, so after determining the node variables need to determine the state of each node in the network, so the sample data for discretization, discretization criteria as shown in Table 3.

Table 3. Affect the state classification of nodes

Indicator name	**Node variable**	**Symbol**	**State classification**	**State classification**
			Status 1 (low)	**Status 2 (high)**
Investment in talent cultivation	The rate of change of national fiscal education funds /%	X1	≤22	>22
	The rate of change in the number of full-time teachers /%	X2	≤6	>6
	Rate of change in the number of books /%	X3	≤16	>16
	The rate of change in per-student educational expenditure /%	X4	≤16	>16
	The rate of change in the floor area of student dormitories /%	X5	≤4	>4
	The rate of change in the school's land area /%	X6	≤5	>5
Investment in scientific research	The full-time equivalent change rate of scientific researchers /%	X7	≤12	>12
	The rate of change in total fixed assets at the end of the year /%	X8	≤12	>12
	The rate of change in internal expenditure of scientific research funds /%	X9	≤21	>21
	The rate of change in the proportion of doctoral students among full-time teachers /%	X10	≤16	>16
	Rate of change in GDP /%	X11	≤16	>16
Talent cultivation output	The growth rate of the total number of students on campus /%	y1	≤6	>6
	The growth rate of the total number of graduates /%	y2	≤6	>6
	Rate of change in degree awarding rate /%	y3	≤6	>6
	Student-teacher ratio growth rate	y4	≤2	>2
Scientific research output	Growth rate of scientific and technological topics	y5	≤12	>12
	The growth rate of published scientific and technological works	y6	≤6	>6
	The growth rate of published scientific and technological works	y7	≤12	>12
	The growth rate of valid invention patents	y8	≤21	>21
	Growth rate of patent transfer	y9	≤32	>32

Evaluation of the performance of vocational education training model input and output generally include both the measurement of efficiency and effectiveness of different factors, according to different needs can be divided into a number of aspects, this paper specifically selected to influence the performance of the indicators shown in Table 3, before the model prediction, it is necessary to classify the state of the relevant indicators. In order to ensure the smooth progress of the study in the selection of input and output factors follow the principle of truth and objectivity, the principle of completeness, scientific and operational principles.

(2) Process and results of discrete variables

Input indicators refers to the assets invested by the state in order to make vocational education schools in order to complete the two main aspects of training students and scientific research, in the text, the main selection of vocational education in Province H scale indicators to analyze, selecting vocational education national financial education expenditure, per capita expenditure on higher education, the end of the year the total value of fixed assets, full-time teachers, teacher-student ratio and so on as the input indicators. Output Effect Indicators: The output effect category is the harvest obtained after the input of vocational education. Specifically including teacher-student ratio, the number of graduates, the number of students, and the output of scientific research papers and other indicators, according to the change in the growth rate of the indicators to determine the state value of the data discretization, the final output of personnel training and scientific research output variables were synthesized into the Y1, Y2 variables. The specific discretization criteria for Y1 and Y2 are as follows: the state values of Y1≥6 and Y1<6 are H and L, respectively. The state values of Y2>8 and Y2<8 are H and L, respectively. The final performance symbol is expressed as Y3, and the discretization criteria for Y3 are: the state value of Y3>12 is H, and the state value of Y3≤12 is L. The process and results of discretization of variables are shown in Table 4.

Table 4. The process and results of discretizing variables

Year	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	Y1	Y2	Y3
2012	A2	A1	A1	A1	A1	A1	A1	A1	A2	A2	A1	H	H	H
2013	A2	A1	A1	A1	A2	A2	A1	A1	A2	A2	A1	L	H	H
2014	A2	A1	A2	A1	A2	A1	A1	A2	A1	A1	A1	L	L	L
2015	A1	A1	A1	A1	A2	A1	A1	A1	A2	A1	A1	H	L	L
2016	A1	A1	A1	A1	A1	A1	A1	A1	A1	A1	A1	L	L	L
2017	A1	A1	A2	A1	A2	A1	A2	A2	A1	A1	A1	H	H	H
2018	A1	A1	A1	A1	A1	A1	A1	A2	A1	A1	A2	L	H	H
2019	A1	A1	A1	A2	A2	A2	A1	A2	A1	A1	A2	H	H	H
2020	A1	A1	A1	A1	A1	A1	A1	A1	A1	A1	A1	H	L	L
2021	A2	A1	A1	A1	A2	A1	A1	A1	A1	A1	A1	H	L	H
2022	A2	A2	A1	A2	A2	A2	A2	A1	A1	A1	A1	H	H	H

3.3.2. Analysis of Key Influential Factors for Bayesian Networks

(1) Predictive reasoning analysis

1) Forward reasoning

According to the data obtained from the collation, the parameter values of the structural early system node variables are calculated. The probability value of each node is imported into the Bayesian network model analysis software GeNle4.0 to carry out Bayesian parameter learning analysis, and the risk state prediction results of each node are collated and obtained as shown in Table 5.

From the results of the parameter learning analysis, it can be seen that 45% of the probability of the input-output performance of the vocational education training model is at a low level, and 55% of the probability is at a high level. In the two output node indicators of talent cultivation and scientific research, the probability of the level of talent cultivation is 58% at a high level and 42% at a low level, and the probability of the level of scientific research is 41% at a high level and 59% at a low level.

Table 5. Prediction results of risk status of each node

Node	(A1) /(L) state probability /%	(A2) /(H) state probability /%
X1	56.00	44.00
X2	85.00	15.00
X3	80.00	20.00
X4	80.00	20.00
X5	38.00	62.00
X6	72.00	28.00
X7	80.00	20.00
X8	64.00	36.00
X9	72.00	28.00
X10	76.00	24.00
X11	78.00	22.00
Y1	42.00	58.00
Y2	59.00	41.00
Y3	45.00	55.00

2) Reverse inference

GeNle 4.0 software also provides the a posteriori probability calculation of the Bayesian network model, which can be used to carry out the corresponding diagnosis of the reverse inference of the Bayesian network model, i.e., when the target node is in the "H" state, the probability distribution of the other nodes in the level of the state. The a posteriori probability results are shown in Table 6.

It can be seen that the inputs and outputs of vocational education training model in province H have a higher probability of low level than high level, and when the final performance level is "H" state, it can be seen that the probability of different indicators is higher than the probability of high level for most of the indicators at the low level. Except for student dormitory area, talent training, scientific research, the existence of "H" state probability value is higher than "L".

Table 6. Posterior probability

Node	(A1) /(L) posterior probability /%	(A2) /(H) posterior probability /%
X1	56.00	44.00
X2	86.00	14.00
X3	80.00	20.00
X4	80.00	20.00
X5	37.00	63.00
X6	72.00	28.00
X7	75.00	25.00
X8	62.00	38.00
X9	72.00	28.00
X10	74.00	26.00
X11	75.00	25.00
Y1	36.00	64.00
Y2	30.00	70.00
Y3	0.00	100.00

(2) Mutual Information Analysis

Mutual information can be simply understood as the amount of information that one of the random variables contains about the other random variable. Or it is the degree of correlation between two random variables and the degree of weakening of the uncertainty of the other random variable Y after determining the value of random variable X. Therefore, the minimum value of mutual information is 0. When the value of mutual information is 0, it means that a given random variable has no relation to the determination of the other random variable.

The results of the mutual information of the node variables for node Y1 are shown in Table 7. It can be seen that for the final sub-node Y1, which is the output of talent training, there is a correlation with other indicators of talent training inputs, and all the values in the column of mutual information are greater than 0, which means that there is a correlation between the indicators of talent training inputs and the indicators of outputs. This indicates that in the vocational education training model of Province H, the output of talent training is affected by different input indicators such as national financial education expenditure, the number of full-time teachers, the total per capita education expenditure, the number of books, the area of student dormitories, the area of the school, and so on.

Table 7. The mutual information result of the node variables of the Y1 indicator

Node	Value of Y1	Mutual info	Percent	Variance of beliefs
X1	Present	0.00006	0.00431	0.0000152
X2	Present	0.00031	0.02914	0.0001061
X3	Present	0.00048	0.04587	0.0001635
X4	Present	0.00024	0.02245	0.0000739
X5	Present	0.00215	0.21432	0.0007153
X6	Present	0.00073	0.08069	0.0002148
X10	Present	0.00046	0.05823	0.0001194

The results of mutual information of node variables for node Y2 are shown in Table 8. It can be seen that the parent node is associated with the final Y2. From the data in the column of mutual information in the table, it can be seen that different parent nodes are related to the final output index Y2, and the values are all greater than 0, which means that the input indexes affecting the outputs of scientific research, such as the full-time equivalent of scientific research personnel, the value of fixed assets at the end of the year, the ratio of doctoral students to full-time faculty members, the internal expenditures of scientific research funds, and the Gross Domestic Product (GDP), etc., influence the number of papers published, the number of academic publications, and the number of patents of inventions, etc., in scientific research. Number of papers published, number of academic publications, number of patents for inventions, etc. Therefore, it can be concluded that in order to improve the scientific research of vocational education in Province H in terms of papers, academic publications and other scientific research it is necessary to increase the investment in full-time equivalents of researchers and increase the investment in the value of fixed assets at the end of the year. The proportion of doctoral students in full-time faculty also increases the number of papers published to some extent and increases the internal expenditure of research funds.

Table 8. The mutual information result of the node variables of the Y2 indicator

Node	Value of Y2	Mutual info	Percent	Variance of beliefs
X7	Present	0.01521	1.904	0.0037248
X8	Present	0.00437	0.452	0.0015242
X9	Present	0.00173	0.179	0.0005023
X10	Present	0.00708	0.905	0.0018425
X11	Present	0.00894	1.163	0.0022849

(3) Sensitivity analysis

Sensitivity analysis is the process of finding the degree of sensitivity that causes a change in the final output variable when one or more of the estimates of all the influencing factors change. The sensitivity analysis quantifies the degree of change in the parameters of the child nodes caused by a change in the parent node, thus identifying the key factors in the Bayesian network model.

The results of the sensitivity analysis of each node of the Bayesian network model are shown in Table 9. Through the sensitivity analysis data, it is known that the top-ranked sensitive indicators are student dormitory area, gross domestic product, full-time equivalent of scientific researchers, the value of fixed assets at the end of the year, internal expenditure of scientific research funds, and the number of doctoral students accounting for the number of full-time faculty members have a greater impact on the final performance than other factors, which suggests that the provincial government of Province H needs to start with the most sensitive indicators if it wants to improve the input and output performance of the vocational education cultivation model of Province H. This is also a good way to improve the performance of inputs and outputs. This indicates that if the government of province H wants to improve the input-output performance of province H's vocational education training model, it needs to start from the most sensitive indicators, which is also the most effective way to improve the input-output performance. In addition, although the national financial education expenditure, the number of full-time teachers, the total per capita education expenditure, the number of books, the school area and other indicators belong to the low-sensitive factor indicators, they should also be emphasized, because these are the basic indicators of the output of talent cultivation, and only by guaranteeing the basic education resources can we guarantee the final output level.

Table 9. Sensitivity analysis of each node in the Bayesian network model

Index node	Sensitivity analysis
X1	0.24
X2	0.82
X3	0.83
X4	0.64
X5	1.52
X6	0.94
X7	15.45
X8	5.93
X9	3.96
X10	9.32
X11	12.15
Y1	0.12
Y2	1.78

(4) Node probability analysis

The conditional probability distribution of each node in the Bayesian network model is derived using the parameter learning function of GeNle 4.0 software. Combined with the constructed Bayesian topological network structure diagram, the focus is on analyzing the conditional probability distribution of the final output variables Y1 and Y2.

The conditional probability distribution of the node Y1 is shown in Table 10. It can be seen that in the case of low level of growth in the number of full-time teachers (X2), low level of growth in the total per capita education expenditure (X3), high level of growth in the area of school dormitories (X5), and low level of growth in the school's footprint (X6), the probability of the final growth rate of talent cultivation occurs the most, at 0.585, and therefore it is considered that if the above four situations occur simultaneously in the input-output process of the vocational education cultivation model Therefore, it is considered that if the above four situations occur simultaneously in the input-output process of vocational education training model, the growth rate of talent training output is the highest. When the number of full-time teachers grows at a low level, the total per capita education expenditure grows at a low level, the school dormitory area grows at a low level, and the school area grows at a low level, the probability of the final growth rate of talent training occurs the smallest, which is 0.476, and it can be seen that the dormitory area of the school has an impact on the final level of talent training.

Table 10. The conditional probability distribution of node Y1

Parent node				Y1	
X2	X3	X5	X6	L	H
A1	A1	A1	A1	0.524	0.476
			A2	0.513	0.487
		A2	A1	0.415	0.585
			A2	0.487	0.513
	A2	A1	A1	0.506	0.494
			A2	0.502	0.498
		A2	A1	0.489	0.511
			A2	0.497	0.503
A2	A1	A1	A1	0.503	0.497
			A2	0.505	0.495
		A2	A1	0.510	0.490
			A2	0.492	0.508
	A2	A1	A1	0.504	0.496
			A2	0.504	0.496
		A2	A1	0.502	0.498
			A2	0.503	0.497

The conditional probability distribution of node Y2 is shown in Table 11. It can be found that when the growth rate of full-time equivalent of scientific researchers (X7) is high, the growth rate of internal expenditure on scientific research (X11) is low, and the growth rate of GDP (X10) is low, the probability of the final growth rate of scientific research output being high is as high as 0.626. When the growth rate of full-time equivalent of scientific researchers is low, the growth rate of internal expenditure on scientific research is low, and the growth rate of GDP is low, the final The probability that the growth rate of scientific research output is high is 0.305, which indicates that scientific research output is high when the growth level of full-time equivalent of scientific research personnel is high. The above analysis shows that some of the indicators have a small probability value for the final inputs and outputs and therefore have a small impact on the performance, while some of the indicators have a large impact and can be identified as key influencing factors.

Table 11. The conditional probability distribution of node Y2

Parent node			Y2	
X7	X11	X10	L	H
A1	A1	A1	0.695	0.305
		A2	0.446	0.554
	A2	A1	0.427	0.573
		A2	0.495	0.505
A2	A1	A1	0.374	0.626
		A2	0.502	0.498
	A2	A1	0.498	0.502
		A2	0.503	0.497

4. Conclusion

In this study, through the comprehensive analysis of DEMATEL-ISM-MICMAC model and Bayesian network, the influencing factors of vocational education talent cultivation present obvious hierarchical and correlation characteristics. Among the 15 influencing factors, the centrality degree of participation in innovation positivity reaches 16.752, ranking first, indicating that innovation consciousness and innovation ability are the core elements of vocational education talent cultivation. The cause degree value of the effect of the guidance of ideological and political spirit reaches 2.261, which has the strongest influence among the driving factors, reflecting the fundamental role of ideological and political education in talent cultivation. Bayesian network analysis shows that when the full-time equivalent growth rate of scientific research personnel is high, the growth rate of internal expenditure on scientific research funding is low, and the growth rate of GDP is low, the probability of the growth rate of scientific research output is high can be up to 0.626, which indicates that human resource inputs are the key factor in enhancing scientific research output. The results of sensitivity analysis show that the sensitivity of student dormitory area is 1.52, which is a relatively low value but has an important position in infrastructure input. Based on the results of the study, it is suggested that government departments should increase the financial investment in vocational education, especially in innovation and entrepreneurship education and the construction of practical teaching facilities; universities should strengthen the integration of industry and education, establish in-depth cooperation mechanisms with enterprises in the housing industry, and enhance the relevance and applicability of talent cultivation; and at the same time, they should construct a diversified talent cultivation quality evaluation system, and take the innovation ability, practical ability and vocational literacy as the Meanwhile, a diversified talent cultivation quality evaluation system should be constructed, taking innovation ability, practical ability and professional literacy as important evaluation indexes, and promoting the continuous optimization and innovative development of vocational education cultivation mode.

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