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A Study on the Prediction of Employment and Entrepreneurship Tendencies of Vocational College Students Majoring in Public Administration Based on Data Mining and the Intervention Mechanism of Ideological and Political Education

Manru Zhou[1,*]
[1] School of Public Administration, Guangdong Vocational Institute of Public Administration, Guangzhou, Guangdong, 510800, China
Corresponding authors: (e-mail: 15876511819@163.com).

Abstract By introducing emerging digital technologies, this study effectively addresses the current challenge of vocational college students' career guidance and entrepreneurship support being disconnected from the talent market. The article is based on the decision tree method in data mining, proposing appropriate decision factor extraction methods tailored to data samples from the employment market and entrepreneurial experiences. A prediction model combining the C4.5 algorithm and CART algorithm is constructed to forecast career and entrepreneurial tendencies, and based on the prediction results, intervention pathways for ideological and political education are proposed. Through the constructed decision tree, the C4.5 algorithm achieved the highest F-value of 0.841 in predicting students' employment tendencies. After the integration of ideological and political education, 88.65% of students believed it could help them further enhance their understanding of future career planning. The data-driven method proposed in this paper for addressing employment and entrepreneurship issues among vocational college graduates has achieved certain.

Index Terms employment and entrepreneurship tendencies, data mining, decision tree, C4.5 algorithm, CART algorithm, ideological and political education

I. Introduction

As employment pressure increases each year, not all university graduates are able to secure positions at their desired organisations, leading to a severe imbalance between labour supply and demand in the job market [1], [2]. To effectively strengthen and improve employment support for vocational college students, it is essential to innovate employment guidance mechanisms, promote the development of student employment initiatives, and enhance both the employment rate and quality of employment for vocational college students [3], [4]. Among these, vocational public administration programmes focus on cultivating students' management skills and public affairs handling capabilities, offering broad applicability and promising career prospects. Although the number of employment opportunities in public administration-related fields has increased with societal development and progress, providing professional management talent across various sectors, the employment rate for vocational college students in public administration-related majors remains between 60% and 70%, and the success rate for entrepreneurship is below 5% [5], [6]. This clearly highlights the lag in current vocational college employment guidance models and underscores the urgency of using student-related data for employment and entrepreneurship forecasting.

In the process of educational digital transformation, vocational colleges have collected student personal information and various behavioural data through teaching management systems and major educational platforms, such as family information, personal interests, academic performance, and internship records, providing data support for exploring students' employment and entrepreneurship tendencies [7]-[9]. Under the framework of course-based ideological and political education, research has indicated that the effectiveness of ideological and political education is correlated with students' career choices. However, the current mechanisms for using ideological and political education to influence students' career choices remain unclear [10]. Data mining (DM) technology offers a potential solution to this issue. DM is a decision-support process that primarily relies on artificial intelligence, machine learning, pattern recognition, statistics, databases, and visualisation techniques to automatically analyse data, make inductive inferences, identify underlying patterns, and predict outcomes based on relevant data. This helps decision-makers adjust strategies, mitigate risks, and make informed decisions [11]-[13].

Currently, regarding the prediction of students' employment and entrepreneurship tendencies, Al-Ajlouni [14] used a method based on the theory of planned behaviour to predict students' entrepreneurial intentions and analysed the factors influencing these intentions. Furthermore, the theory of planned behaviour can be used to explore variations in students' intentions. Ren [15] utilised the k-means clustering algorithm to analyse the key influencing factors of students' career development. By combining a long short-term memory network model with four years of time-series data, they predicted students' career preferences and provided personalised career development guidance based on these predictions. Tu et al. [16] employed random forest, support vector machines, sine-cosine algorithms, and chaotic local search to respectively select key factors influencing entrepreneurial intentions, construct factor-selection decision models, adjust model parameters, and enhance the search performance of sine-cosine algorithms, thereby predicting students' employment or entrepreneurial intentions. Wei et al. [17] adjusted the kernel extreme learning machine using a Gaussian basic strategy-enhanced Harris eagle optimiser to construct a model for predicting students' entrepreneurial tendencies. Compared to basic machine learning methods, this model is more effective.

Similarly, Zhang et al. [18] created a kernel extreme learning machine model optimised by an enhanced raven search algorithm to predict students' entrepreneurial tendencies, achieving a prediction accuracy of 93.2%. Xia et al. [19] developed a bias-aware graduate employment tendency prediction architecture targeting employer unconscious bias, using gradient-penalised Gaussians, time-convolutional networks, and regularisation methods. Raj and Manivannan [20] established a logistic regression prediction classification algorithm to predict students' entrepreneurial tendencies and improved the model's accuracy through feature selection, but the model's predictions were based solely on simple questionnaire data. Garodia et al. [21] shared multiple machine learning algorithms for predicting students' entrepreneurial tendencies, with the study showing that random forests yielded the best prediction results, achieving an accuracy rate of 83%. However, Trujillo et al. [22] introduced machine learning (random forest, support vector machine, and neural network) for predicting students' career-related tendencies. While these models demonstrate some effectiveness, they lack the inclusion of public data and longitudinal data. Sun et al. [23] analysed and predicted the employment status of vocational college students using MD technology, primarily by combining decision tree algorithms and association rule mining algorithms to construct predictive models and analyse employment status (including employment intentions).

This paper first explores the feasibility of data mining algorithms in predicting employment outcomes for vocational college students majoring in public administration. The C4.5 algorithm is selected to classify and analyse employment-related data of graduates. Using Python as the programming language and Excel as the database for storing sample data, an employment tendency prediction model is constructed. Next, the Gini coefficient is used to measure the data, and the CART algorithm is employed to build a decision tree to identify the key factors influencing graduates' entrepreneurial intentions. The most influential factors are selected to support the prediction of entrepreneurial tendencies. Finally, based on the prediction results, the underlying mechanisms influencing the data are discussed, and intervention pathways for integrating ideological and political education into vocational students' employment and entrepreneurship education guidance are proposed. The effectiveness of these interventions is analysed through questionnaire surveys.

II. Prediction of student employment and entrepreneurship based on decision trees

II. A. Methods for predicting student employment

II. A. 1) Algorithm Selection

The ID3 algorithm introduces some concepts from information theory, using information entropy and information gain as the basis for classifying data attributes, thereby achieving classification of the data set.

Entropy can be used to describe the degree of uncertainty of a random variable.

Let X be a discrete random variable with the following probability distribution:

$$p(x_i)=P(X=x_i), i=1,2,3,\ldots,n \tag{1}$$

Define the entropy H of a random variable X as:

$$H(X)=E(I(X))=\sum_{J}^{n}[p(x_i)\cdot I(x_i)]=\sum_{i}^{n}[p(x_i)\cdot\log(\frac{1}{p(x_i)})] \tag{2}$$

The entropy of a random variable X depends on the distribution of X, as agreed in $0\cdot\log 0=0$.

Conditional entropy is the uncertainty of Y given the known conditions of $H(Y|X)$ in X, defined as:

$$H(Y|X)=\sum_{x=X}[p(x_i)\cdot H(Y|X=x)] \tag{3}$$

Information gain is the extent to which the entropy value of Y decreases when X is known, compared to when no conditions are specified. It is defined as:

$$Gain(Y,X) = H(Y) - H(Y \mid X) \tag{4}$$

The difference between information entropy and conditional entropy is information gain. Generally, the larger the information gain, the greater the ‘increase in purity’ obtained by the partitioning attribute used. The ID3 algorithm uses this to select the partitioning attribute for decision trees, and is generally used to process discrete data. From the information gain formula, it can be seen that this algorithm tends to favour features with higher values.

The C4.5 algorithm was developed as an improvement to the ID3 algorithm, with information gain rate serving as the criterion for selecting splitting attributes. All the advantages of the ID3 algorithm are retained in the C4.5 algorithm. Additionally, the C4.5 algorithm can handle both discrete and continuous variables, eliminating the ID3 algorithm's bias toward features with multiple values. Compared to the ID3 algorithm, the C4.5 algorithm also achieves significant improvements in efficiency and accuracy.

The information gain rate takes into account the ‘cost’ incurred to obtain information gain, eliminating the impact of features with a large number of values. It is defined as the information gain divided by the intrinsic value of the feature, defined as:

$$GainRatio(Y,X) = \frac{Gain(Y,X)}{H(X)} \tag{5}$$

Determine the information gain rate of each attribute, select the attribute with the highest information gain rate as the root node, and iterate using this standard to ultimately construct a classification decision tree.

This paper uses the C4.5 algorithm to perform classification analysis on data related to graduate employment. It mainly explores the feasibility of this algorithm in predicting the employment of graduates from applied universities. By establishing an employment prediction model, it is hoped that this will provide assistance to universities in carrying out employment guidance work.

II. A. 2) Determination of tools

To address the cumbersome calculations resulting from large data samples and numerous test attributes, this study is based on the core ideas of the C4.5 algorithm, using Python language and Excel as the database for storing sample data, to design and develop a simple college student employment prediction tool.

Python has been widely applied in the field of machine learning. The college student employment tool developed using this language primarily has the following functions:

(1) Building predictive models: The tool automatically generates decision tree predictive models and extracts corresponding classification rules by selecting pre-prepared training sample sets, i.e., reading Excel data tables.

(2) Evaluating the predictive accuracy of the model: Based on the generated predictive model, the tool can read test samples, generate predictive results based on the test attributes in the samples, and compare the predictive results with actual employment outcomes. It then calculates the number of samples with consistent results and the number of samples with inconsistent results, thereby determining the predictive accuracy rate of the model.

(3) Conduct prediction applications: The prediction model is constructed based on historical employment data of university students. For future students' employment situations, as long as there are complete prediction attributes, this tool can generate corresponding prediction results.

II. B.Methods for predicting student entrepreneurship

II. B. 1) Selection of branch variables and split points

The ideal result of a classification tree is that each leaf node in the tree is either a pure node (where all samples within the node belong to the same class) or very small (where the number of samples within the node is less than a predefined value n). When selecting the optimal grouping variable from a large number of predictor variables, the CART algorithm uses the Gini index for evaluation. The smaller the Gini coefficient, the purer the node, and thus the predictive variable is the optimal split point for the current attribute.

Let the sample set T contain n classes. The Gini index measures the impurity of data partitioning, defined as:

$$gini(T) = 1 - \sum_{i=1}^{n} P_i^2 \tag{6}$$

Among them, p_i is the probability that T contains C_i classes. If the binary split of A divides T into two subsets T_1 and T_2, then the Gini index of this division is:

$$Gini_A(T) = \frac{|T_1|}{|T|}Gini(T_i) + \frac{|T_2|}{|T|}Gini(T_2) \tag{7}$$

For discrete attributes, determine whether $A \in S'$ holds, where S' is a subset of all values of attribute A. Select the subset that produces the minimum Gini index as its split subset. For continuous attributes, the midpoint between each pair of adjacent values is taken as a possible split point. For a possible split point V of A, T_1 is the set satisfying $A \le V$, while T_2 is the set satisfying $A > V$. The point that produces the minimum Gini index is selected as the split point for the attribute.

The binary split of a continuous or discrete attribute A will result in a reduction in impurity to:

$$\Delta Gini(A) = Gini(T) - Gini_A(T) \tag{8}$$

The attribute that maximises impurity reduction (or has the smallest Gini index) is selected as the split attribute. This attribute, together with its split subset or split point, forms the split criterion.

II. B. 2) Tree pruning

Due to noise and outliers in the data, many branches reflect anomalies in the training data. Pruning methods can address the issue of overfitting in such data by removing unreliable branches, thereby improving the tree's classification ability. CART employs a post-pruning method, which involves removing branches from a node and replacing them with leaves to prune the subtree of a given node. CART uses the principle of minimising cost-complexity to perform pruning.

This method first generates a tree where the terminal nodes have pure (or nearly pure) category members. At this stage, the tree has many levels and leaf nodes. Let this tree be denoted as $T_{\max}$. The overall misclassification rate of the tree can be defined as:

$$R(T) = \sum_{t=1}^{n} R(t) = \sum_{t=1}^{n} (\min_{i=1}^{k} \sum_{j=1}^{k} C_{ij} p(j \mid t) p(t)) \tag{9}$$

where $R(T)$ is the overall misclassification rate of the tree, $R(t)$ is the misclassification rate of the tth node, n is the number of leaf nodes, k is the category tree of the samples in the current node, $p(j \mid t)$ is the probability of sample j in node t, C_{ij} represents the loss of judging sample i as sample j, and $p(t)$ is the probability of each sample being assigned to node t.

The CART pruning algorithm is used. The system cost-complexity measure is defined as:

$$R_\alpha(T) = R(T) + \alpha * Leafcount(T) \tag{10}$$

Where α is a constant representing the cost of the complexity of each terminal node, $Leafcount(T)$ is the number of leaf nodes in the tree, and $R\alpha(T)$ is understood as the composite cost of the weighted error rate of the tree and the sum of the complexity penalty values.

II. B. 3) Data collection on vocational college students' entrepreneurship

This paper collects data from 450 students majoring in public administration at higher vocational schools, vocational universities, and other higher vocational institutions. It surveys each student's personal background, personal characteristics, environmental factors, and entrepreneurial tendencies. Due to space limitations, the following only explains the data appearing in the decision tree, which includes personal background such as gender, major, monthly family income, level of business knowledge, and level of entrepreneurial education received. Personal traits include the willingness to take risks and attitude towards challenges. Environmental factors encompass the level of support for entrepreneurship from three aspects: society, school, and family. Examples include establishing entrepreneurship funds, hosting entrepreneurship competitions, attracting venture capital, participating in entrepreneurship activities, and the university providing supporting measures and services for entrepreneurship. Family, relatives, and friends also provide support for graduates' entrepreneurship endeavours. The survey on entrepreneurial inclinations examined two aspects: whether the student has prior entrepreneurial experience and whether they plan to start a business in the future.

III. Empirical analysis of employment and entrepreneurship tendencies among higher vocational students

III. A. Employment Trend Prediction Analysis

III. A. 1) Clustering of influencing factor data

The results of the data clustering analysis are shown in Table 1. Taking the 4-class example, the Silhouette value of the information entropy method is 0.23573, which is lower than that of the non-dimension-reduction method but higher than that of the average score and GPA. By calculating and comparing the Silhouette values of the clusters to evaluate clustering effectiveness, it is evident that the clustering effectiveness of traditional average scores and GPA is inferior to that of the unshrunk and information entropy scores. Although the clustering effectiveness of the information entropy scores is lower than that of the unshrunk method, the number of features involved in the clustering is fewer than in the unshrunk method, the clustering efficiency is higher than that of the non-dimension-reduction method. Therefore, using the information entropy method for feature reduction and value reduction of grades is reasonable and feasible.

Table 1: Comparison of Silhouette values for each clustering scheme

Nature of the Course	Expected number of clusters	3	4	5	6	7
Professional foundation Correction of grades	Information entropy	0.22337	0.23573	0.27675	0.29816	0.23589
	No dimension reduction	0.29849	0.27051	0.23832	0.26148	0.2899
	Average score	0.18396	0.10978	0.17595	0.1819	0.08358
	Grade Point Average	0.03363	0.06247	0.1205	0.17293	0.1409

III. A. 2) Influence factor scores

Using Python software, data mining was performed using the DecisionTreeClassifier in the sklearn module. To avoid overfitting due to excessive decision tree branches, 5-fold cross-validation was used to verify that when the maximum depth max_depth was set to 6 and min_samples_split was set to 12, the decision tree could fit the training set data well and predict the test set data well. Using the SelectKBest feature selection function in sklearn.feature_selection, the importance of attribute columns is shown in Figure 1. The attribute scores range from 2 to 86, with the highest value being graduation time. This may be because employment status is closely related to the employment market conditions of that year.

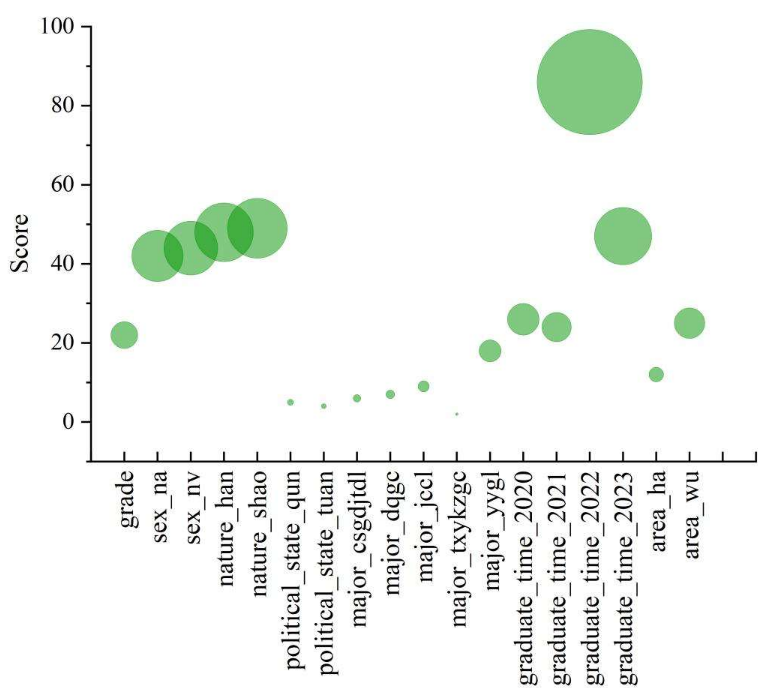

Figure 1: Determine the importance of the attribute columns

III. A. 3) Comparative Analysis of Data Mining Performance

To determine the practicality of the employment prediction model for vocational college students established using the decision tree algorithm, a 4x4 table was used as the data foundation. The performance of the decision tree algorithm was evaluated using five evaluation indicators: precision rate, recall rate, accuracy rate, F-value, and precision. The precision indicator was calculated using the harmonic mean of the F-value, defined as the harmonic mean of the accuracy rate and F-value.

In this study, TP (true positive) refers to true positives, i.e., samples where the actual result is ‘employed’ and the data mining result is also ‘employed.’ TN (true negative) refers to true negatives, i.e., samples where the actual result is ‘unemployed’ and the data mining result is also ‘unemployed.’ FP (false positive) refers to false positives, i.e., samples where the actual result is “unemployed” but the data mining result is ‘employed.’ FN (false negative) refers to false negative cases, i.e., the number of samples where the actual result is ‘employed’ and the data mining result is ‘unemployed.’

The higher the precision rate, the better the sensitivity of the algorithm. The higher the recall rate, the better the sensitivity of the algorithm. The higher the accuracy rate, the higher the accuracy of the algorithm. The higher the precision, the better the precision of the algorithm. The larger the F-value, the better the overall performance of the algorithm.

Based on the decision tree algorithm model, 35% of the sample population was used as the test set for evaluation, and the corresponding evaluation metrics were calculated. The results are shown in Table 2. Overall, the C4.5 algorithm had the highest F-score (0.841) and the best overall performance.

Table 2: Performance indicators of decision tree algorithm

	Precision	Recall	Accuracy	F
C4.5	0.854	0.965	0.907	0.841
ID3	0.95	0.85	0.894	0.801
CART	0.822	0.811	0.975	0.818
Adaboost	0.857	0.837	0.996	0.814
Xgboost	0.994	0.884	0.994	0.821
GBDT	0.979	0.904	0.896	0.831

III. B. Prediction and analysis of entrepreneurial tendencies

Within the established testing environment, spatial clustering classification is determined based on the scope covered by data mining. Similarly, the corresponding entrepreneurial clustering data processing information is first obtained, and a corresponding classification structure is established to calculate the data clustering convergence ratio.

Based on the obtained ratio, corresponding processing regions are defined within the data classification model, which can be roughly divided into application processing regions and restricted processing regions. Based on the data changes in these two regions, the specific data fluctuation frequency changes are plotted. The data fluctuation frequency of entrepreneurial influence factor data classification is shown in Figure 2. Among them, Test Group 1 uses the traditional linear regression data classification processing method, Test Group 2 uses the traditional object data classification processing method, and Test Group 3 uses the data mining method designed in this paper.

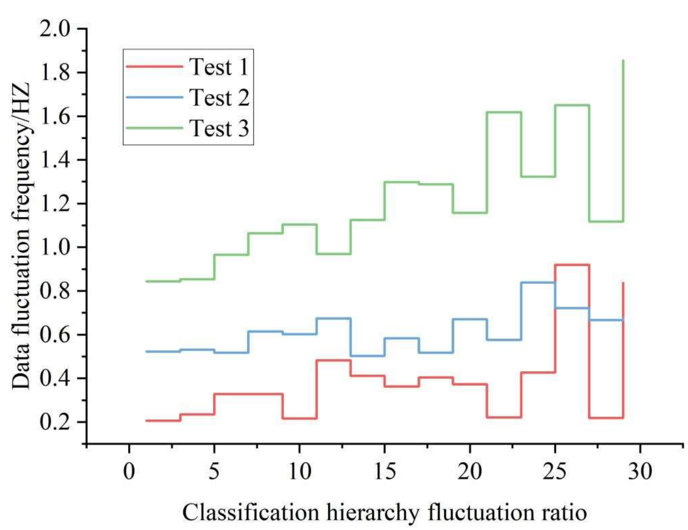

Figure 2: Data decision classification - Data fluctuation frequency

Based on the above figure, it is possible to gain an understanding of the fluctuations in innovation and entrepreneurship data. Subsequently, by combining the actual data classification requirements of R vocational colleges and the range of changes in innovation and entrepreneurship, the actual misclassification rate is calculated. Through calculation, the actual misclassification rates for the three test groups are shown in Table 3. Compared to the traditional test group, the misclassification rate obtained using the method designed in this paper is relatively low (averaging only 14.43%), indicating that it achieves better classification results for innovation and entrepreneurship data at P vocational colleges, demonstrating practical application effectiveness, and enabling more precise prediction of entrepreneurial tendencies among students in public administration-related majors at vocational colleges.

Table 3: Performance indicators of decision tree algorithm (%)

Test group	Test 1	Test 2	Test 3
1	33.552	32.03	17.449
2	34.142	32.567	13.821
3	31.992	33.905	11.944
4	33.089	35.056	15.827
5	28.038	35.691	11.58
6	28.475	35.867	19.031
7	31.214	34.873	16.588
8	30.808	32.527	12.025
9	29.839	32.548	14.257
10	30.792	34.8	9.762
11	31.467	30.807	14.484
12	28.382	34.356	17.58
13	29.867	40.433	16.591
14	26.052	31.889	13.203
15	36.26	31.437	12.308

IV. The intervention mechanism and effectiveness of incorporating ideological and political education into student employment and entrepreneurship

IV. A. Pathways for ideological and political education to influence student employment and entrepreneurship

Based on the aforementioned predictive analysis of students' employment and entrepreneurship tendencies, particularly the findings regarding relevant influencing factors, higher vocational colleges should guide students in developing correct career choice and employment/entrepreneurship concepts, helping them gain a more objective understanding of their future employment directions. In teaching, ideological and political education courses and employment guidance courses can complement and support each other in terms of curriculum design and teaching content. By integrating the theoretical knowledge, ideological concepts, and practical activities of ideological and political education into career guidance courses, and implementing teaching in a phased and hierarchical manner, students can become more rational, confident, and effective in their learning and employment processes, and develop a scientific understanding of job seeking and career development planning. From the moment students enrol, they should be provided with professional and targeted career guidance to ensure that they develop correct employment perspectives and professional ethics throughout their entire learning period. Higher education institutions should pay close attention to students' mental health during the teaching process. Currently, many students exhibit psychological issues such as self-centredness, low self-esteem, timidity, and a tendency to idolise foreign cultures. These issues directly impact students' future career choices and employment prospects. Therefore, while conducting ideological and political education, it is crucial to closely monitor students' psychological well-being, promptly address their anxieties and confusions during job hunting and employment, and provide care and support to help them effectively manage psychological challenges, laying a solid foundation for their future careers.

IV. B. Cognitive Analysis of Student Employment and Entrepreneurship from the Perspective of Ideological and Political Education

IV. B. 1) Public Perspective

The study aimed to thoroughly analyse students' perceptions of employment and entrepreneurship within the context of ideological and political education. To this end, a survey was first conducted among the general public. The public's attitudes towards vocational college students' employment and entrepreneurship are shown in Figure 3. Most respondents expressed support for student entrepreneurship, with 53.85% indicating ‘support’ and 24.75%

indicating ‘strong support.’ This indicates that over 78% of respondents support college students' entrepreneurship, reflecting widespread societal recognition of entrepreneurial spirit among students. To further promote entrepreneurship among vocational college students, it is recommended to provide entrepreneurship education and training to enhance their entrepreneurial knowledge and skills, enabling them to better understand the challenges and opportunities involved in the entrepreneurial process. Establish entrepreneurship support platforms and create more incubators and support platforms to provide vocational college students with funding, resources, and guidance to help them realise their entrepreneurial dreams. By showcasing successful entrepreneurship cases among vocational college students, promoting these success stories, and inspiring more students to participate in entrepreneurship, role models can be established. By encouraging collaboration between vocational colleges and enterprises, providing internship opportunities and practical experience, students can hone their entrepreneurial skills in a practical environment, further enhancing their entrepreneurial enthusiasm and success rates, and fostering an entrepreneurial atmosphere.

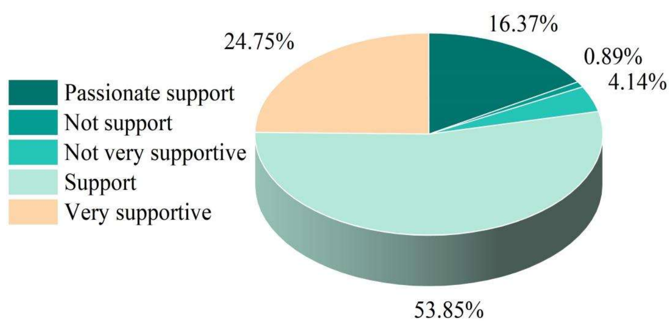

Figure 3: Public attitudes towards vocational college students' entrepreneurship

IV. B. 2) Students' self-awareness of professional skills and suitability

Before and after implementing ideological and political education teaching interventions, a questionnaire survey was conducted on the selected sample students. The employment and entrepreneurship perceptions of vocational college public administration students are shown in Table 4. After graduation, graduates tend to choose ‘majors closely related to their field of study,’ accounting for 34.28%. ‘Majors generally related to their field of study’ account for 45.42%. ‘Majors unrelated to their field of study’ account for 11.15%. ‘Professions completely unrelated to their major’ accounted for 9.15%. The adaptability of knowledge and skills related to future careers is perceived as ‘very weak’ by 10.65%, ‘relatively weak’ by 16.58%, “average” by 56.24%, ‘relatively strong’ by 13.21%, and ‘very strong’ by 3.32%. It can be seen that over half of the students believe that the adaptability of the knowledge and skills they have learned to future positions is ‘average.’ Those with good work ability, coordination ability, endurance, basic problem-solving ability, professional knowledge, and skills, etc., account for over 60%. After integrating ideological and political education into students' employment and entrepreneurship education guidance, over 85% believe it was helpful.

Table 4: Students' professional skills and matching situation

Professional relevance	Very relevant	Generally relevant	Basically irrelevant	Completely irrelevant	-
%	34.28	45.42	11.15	9.15	
Understanding of professional skills	Very weak	Relatively weak	Average	Relatively strong	Very strong
%	10.65	16.58	56.24	13.21	3.32
Employment market adaptation	Very capable	Generally	Doubt	Negative	-
%	8.65	35.31	46.32	9.72	8.65
The role of ideological and political education	Very helpful	Somewhat helpful	Generally	Basically no help	Negative impact
%	14.21	45.5	28.94	10.24	1.11

V. Conclusion

The article applies data mining techniques to the observation of student employment and entrepreneurship guidance.

Based on the mining results, it proposes integrating ideological and political education into the employment and entrepreneurship education of vocational college students majoring in public administration. The mining results indicate that the attribute scores influencing students' employment and entrepreneurship tendencies range from 2 to 86, with the highest value being graduation time. This fully demonstrates that, whether it is employment or entrepreneurship, graduates' careers are always closely related to changes in market demand. This suggests that we should organically integrate ideological and political education with employment and entrepreneurship guidance, strengthening the connection between ideological and political education and employment and entrepreneurship. This helps students understand the relationship between national strategy and personal career development from an ideological perspective. Through such course design, students not only acquire practical skills in employment and entrepreneurship but also gain a deeper understanding of the social significance of their career choices from an ideological perspective, thereby integrating their personal development into the broader national development framework and enhancing their sense of mission and responsibility. Additionally, higher vocational colleges should innovate educational methods to enhance the interactivity and practicality of education, stimulate students' interest in learning, and improve teaching effectiveness. This allows students to deepen their understanding of ideological and political theory and employment and entrepreneurship practices through participation, thereby stimulating their interest and initiative in learning.

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