Research on Early Warning of Entrepreneurial Risks and Enhancement of Employment Competitiveness for College Students Driven by Big Data Algorithm Model and Application Validation

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ABSTRACT Accurate prediction of entrepreneurial risks and enhancement of employment competitiveness are essential for improving student career development outcomes in dynamic labor markets. This study proposes an integrated framework combining multi-source data fusion, time-series risk assessment, and intelligent recommendation algorithms. Student digital profiles are first constructed through heterogeneous campus data integration. A temporal early-warning model is then developed to identify entrepreneurial risks dynamically, while graph neural networks and reinforcement learning are employed to generate personalized employment capability enhancement pathways. Experimental results indicate that the proposed model achieves an entrepreneurial risk prediction accuracy of 88.7% and provides effective early-warning capability. Real-world validation further demonstrates improvements in entrepreneurial survival rates, employment matching, and career competitiveness. The study offers a data-driven solution for talent development and provides methodological references for predictive analytics, intelligent recommendation systems, and information fusion technologies.

INDEX TERMS entrepreneurial risk prediction, employment competitiveness, information fusion, intelligent recommendation, predictive analytics

I. INTRODUCTION

As the rapid expansion of higher education intersects with the structural shifts in the industry, the challenges of low entrepreneurial success in advanced materials and diminished competitiveness in technical roles have become increasingly severe. This widening gap highlights the urgent need for graduates to master specialized processing innovations to navigate a tightening and more complex job market [1,2]. Traditional entrepreneurship guidance relies heavily on experience judgment and static questionnaires, with scattered data sources and lagging updates, making it difficult to identify the hidden risks of entrepreneurial projects in the early stages; employment services generally adopt a generalized training model, ignoring the differences in individual student abilities and dynamic market demands, resulting in a lack of targeted training paths. The rapid development of big data technology has provided new possibilities for realizing full-cycle student profiles, dynamic risk monitoring, and personalized ability enhancement. How to effectively integrate multi-source campus data and construct intelligent algorithm models has become a key issue that needs to be addressed in the field of precise education in universities [3]. Existing research has actively explored the early warning of entrepreneurial risks and the enhancement of employment competitiveness for college students. Donaldson et al., based on the case of eight student entrepreneurs in Valencia, Spain, revealed how the context affects the generation and interpretation of financing signals from the perspective of the entrepreneurial ecosystem [4]. Brzozowska et al. surveyed 295 local and international students at four universities in Opole, Poland, comparing their entrepreneurial intentions and risk attitudes, and incorporated cultural and immigration factors into the theory of planned behavior to fill the gaps in related research [5]. Hernández et al. proposed a method based on polymorphic set theory to measure the degree of implementation of entrepreneurial ability training strategies and their contribution to the quality and ability of future college graduates, in order to characterize the contradictions and uncertainties in the dynamic interaction of multiple factors [6]. Against the backdrop of increasing employment pressure on college students, Zhi proposed a method to support the matching analysis based on student profiles and job requirements, and explored and proposed the application of fuzzy clustering algorithm in the assessment of college students' mental health [7]. Qian et al., based on the definition of graduates with employment difficulties, analyzed their employment status and causes from the perspectives of recent graduates and non-recent graduates, providing a new research perspective on the employment problem of college graduates [8]. However, the above studies are often limited to a single data source, lack in-depth modeling of the temporal evolution characteristics of entrepreneurial projects, and the employment recommendations are mostly static matching, making it difficult to dynamically adjust the improvement path according to the development of students' abilities. Overall, the existing methods still have obvious shortcomings in terms of the breadth of data fusion, the depth of temporal feature mining, and the flexibility of personalized path planning. To address the aforementioned issues, some studies have attempted to introduce deep learning and recommendation system technologies to improve model performance. For example, Wang et al. constructed an evaluation model based on backpropagation neural networks to address the problems of bias and inefficiency in innovation and entrepreneurship teaching evaluation, thereby improving the evaluation of teaching effectiveness and practical guidance capabilities [9]. Gnoh et al. aimed to improve the operational sustainability of higher education institutions by using artificial intelligence and prediction technologies, focusing on student enrollment scale prediction and model construction, and expanding the application research of artificial intelligence in university management [10]. However, most existing methods separate risk warning from employment improvement, failing to construct an integrated "monitoring-early warning-feedback-optimization" closed-loop mechanism, and the interpretability and practical application verification of the models are relatively weak. To this end, this paper proposes a comprehensive algorithm model for entrepreneurial risk warning and employment competitiveness improvement driven by big data. By integrating multi-source campus data, a time-series early warning model and a personalized recommendation algorithm are designed, and application verification is carried out on a real campus platform to make up for the shortcomings of existing research in terms of systematicness and operability.

This paper intends to design and validate an algorithm model system to enhance the entrepreneurial success rate and employment competitiveness of college students. First, this paper collects data from academic affairs system, entrepreneurship incubation system, internship database, and recruitment website to construct digital student profiles based on students' whole learning experience. Second, an ensemble model based on Bi-LSTM and XGBoost with attention mechanism is designed to dynamically evaluate the risks of entrepreneurship project and make early warning. Third, graph neural networks and reinforcement learning algorithms are designed to construct dynamic matching paths between students' employability and job requirements and then generate skill enhancing suggestions according to individual differences. Finally, a quasi-experimental study based on real campus data platforms is designed to validate the effectiveness of the models. Experimental results demonstrate that this research provides operable technical support for building a digital education closed loop within textile engineering departments, offering novel insights for the cross-integration of risk management theory and informatics. By leveraging educational big data, this approach establishes a data-driven framework for navigating the technical complexities and market uncertainties inherent in high-performance research and industrial application.

II. MULTI-SOURCE CAMPUS DATA COLLECTION AND CLEANING

The raw data for this study were extracted from the academic management system of participating universities, university student entrepreneurship incubation base, internship and training base database, and public data interface of main recruitment website. The data collection covers four years of undergraduate and vocational college students. Data content includes five types of basic modules:

1) Student basic information: demographic information such as major, year, and place of origin;

2) Academic track: course grades, competition awards and skills certificates;

3) Entrepreneurship project log: project plans, monthly operation report, investment and financing records and team change records;

4) Internship and employment data: internship unit evaluation, employment destination and salary;

5) External environment data: industry recruitment data, job skill requirements and regional entrepreneurship policy.

We collected about 3.2 million raw data records of 12,483 students in total.

Data cleaning is carried out in the following four steps:

1. Deduplication and consistency verification: because the student data come from multiple sources, the same student may appear in multiple data sets. In this step, we merged the duplicate data from different sources and unified the naming rules of key fields such as student ID and project number. 2. Missing value handling: multiple imputation is used to fill in continuous variables such as academic performance and internship evaluation. Items with a large number of missing values in the startup log are deleted, and a sample of start-up projects with continuous records for at least 6 months is retained. 3. Detection of outliers. We use box plots and clustering algorithms to detect outliers in salary and funding amount fields and make corresponding corrections. 4. Data anonymization and standardization. The name, student ID and national ID number of sensitive personal information are

anonymized. Unstructured text data (such as business plans and internship comments) are converted into TF-IDF feature vectors. After cleaning, a structured dataset containing 4,600 entrepreneurial project samples and 8,500 employment behavior samples was established. The entrepreneurial sample represents students who had initiated a registered startup or an incubation project with continuous operational records of at least six months. The remaining 7,883 students (63.2% of the total) either did not participate in entrepreneurial activities or had incomplete records that did not meet the inclusion criteria. Similarly, the employment behavior sample consists of students with complete internship and job placement records, excluding those with missing or unverifiable employment data. These samples were derived from the total population of 12,483 students, with partial overlap between the two sample sets (i.e., students who both engaged in entrepreneurial activities and had employment records were included in both analyses).

III. CONSTRUCTION OF TIME-SERIES FEATURES FOR STARTUP RISK

Feature construction based on months as the basic time unit, output equally spaced time series of each startup project from the start-up date to current month. First, from the view of team stability, the number of team member change, the number of core member leave, the team size change rate are statistic analysis by month. After that, just take the first order differencing on above three indicators to reflect the sudden change. Second, from the view of financial health, monthly total expenditure, amount of financing received, cash flow balance are multiplied into the integral to get cash consumption rate and the risk index of broken capital chain (based on the number of month that existing money can sustain). Third, from the view of market response, product iteration count, user growth, active user ratio, marketing return on investment are extracted, exponential smoothing is used to remove the seasonality. Fourth, from the view of policy matching, a policy matching score of each project is calculated by month based on the textual similarity between the industry of the project and the entrepreneurial support policy of its region. The project matching score is obtained by TF-IDF and cosine similarity algorithm.

Finally, we only retain the project sample that can form a continuous record for at least 6 months. For the project with missing value in certain month, we use linear interpolation and the average of adjacent month to fill the missing value. At the same time, we also add static feature of project launch duration, initial team size, project industry type into each time point, and output the 64 dimensional time series feature vector. Finally, the data were first split chronologically into training set (70%), validation set (15%), and test set (15%) while preserving temporal order. The mean and standard deviation computed from the training set were then used to standardize all features in the training, validation, and test sets separately. This procedure prevents data leakage by ensuring that no information from the validation or test sets influences the scaling of the training data.

IV. EARLY WARNING MODEL DESIGN INTEGRATING ATTENTION MECHANISMS

Is the amount of startup project risk evolution contributed by indicators at time step t to the final success or failing. Traditional time-series models have limited ability to model sudden changes at these time steps. In this paper, we design a model integrated with Bi-directional long short-term memory network (Bi-LSTM), attention mechanism and XGBoost for dynamic prediction of start-up project risk probability at time step. The whole model has two parallel branches. The one based on chronological features, whose input is monthly feature vector sequence constructed in section 2.2 with dimension of T×64 (T means the number of months the project has run). Stacked two-layer Bidirectional LSTM encodes the sequence in a forward and backward direction, with 128 hidden units in each layer. It can capture the past and future information of sequence by bidirectional propagation process. The forward propagation process of Bi-LSTM layer can be formally described as (1-3):

$$\vec{h}_t = \mathrm{LSTM}_{\mathrm{fwd}}(x_t, \vec{h}_{t-1}) \tag{1}$$

$$\overleftarrow{h}_t = \mathrm{LSTM}_{\mathrm{bwd}}(x_t, \overleftarrow{h}_{t+1}) \tag{2}$$

$$h_t = [\vec{h}_t; \overleftarrow{h}_t] \tag{3}$$

Where, x_t is the input feature vector at time t, and $\vec{h}_t$ and $\overleftarrow{h}_t$ are the forward and backward hidden states, respectively. The two are concatenated to obtain the complete hidden state h_t at time t. Subsequently, an attention mechanism is introduced to weight and sum the outputs of the Bi-LSTM at each time step. The weights are calculated using a learnable attention scoring function, aiming to amplify the contribution of high-risk time nodes. The output of the attention layer is then dimensionality-reduced by a fully connected layer to generate a risk score for the temporal features.

The second branch processes static features, including 11 non-temporal variables such as project start-up time, initial team size, and industry category. The XGBoost algorithm is used to construct a gradient boosting tree model, leveraging its advantage in handling heterogeneous data and feature interactions to output a risk probability based on static features.

The outputs of the two branches are integrated using a soft voting strategy. The probability outputs P_{lstm} of the Bi-LSTM branch and P_{xgb} of the XGBoost branch are assigned weights α and 1-α, respectively, and the weighted sum is used to obtain the final risk probability P_{final}. The model training uses binary cross-entropy as the loss function, Adam as the optimizer, with an initial learning rate of 0.001 and a batch size of 64. An early stopping mechanism terminates training when the validation set loss does not decrease for five consecutive rounds. Rather than adopting a fixed threshold of 0.5, the optimal decision threshold was determined empirically based on the validation set using the Youden index (J = sensitivity + specificity - 1), which balances true positive and false positive rates. The selected threshold was 0.43, yielding the maximum F1 score on the validation set. This threshold is then applied to the test set to classify projects as high-risk. For practical implementation, the model outputs a continuous risk probability, allowing educators to adjust the threshold according to their risk tolerance and available intervention resources. The time point when the selected threshold is first exceeded is recorded as the warning time. The key parameters of the model are configured as shown in Table 1.

TABLE 1. Core Parameter Configuration of the Early Warning Model

Module	Parameter	Value
Bi-LSTM layer	Number of hidden units	128
Bi-LSTM layer	Number of layers	2
Bi-LSTM layer	Dropout rate	0.3
Attention mechanism	Attention dimension	64
XGBoost branch	Learning rate	0.1
XGBoost branch	Maximum depth	6
XGBoost branch	Number of trees	200
Ensemble strategy	Temporal branch weight α	0.6
Optimizer	Optimization algorithm	Adam
Training parameters	Initial learning rate	0.001
Training parameters	Batch size	64

V. EMPLOYMENT COMPETENCY PROFILE AND PERSONALIZED PATH GENERATION

The graph neural network module is used to construct a student employment competency profile. Elements such as students, courses, internship experience, skill tags, and job requirements are mapped to heterogeneous graph nodes. Using course selection relationships, internship participation, skill associations, and job suitability as edges, a heterogeneous information network containing six types of nodes and eight types of relationships is constructed. R-GCN (Graph Convolutional Network) is used to learn the embeddings of nodes, updating the vector representation of student nodes by aggregating neighbor node information. The node update rule is (4):

$$h_i^{(l+1)} = \sigma\left(\sum_{r\in R}\sum_{j\in N_i^r}\frac{1}{c_{i,r}}W_r^{(l)}h_j^{(l)} + W_0^{(l)}h_i^{(l)}\right) \tag{4}$$

Where, $h_i^{(l)}$ is the embedding representation of node i at layer l, R is the set of relationship types, N_i^r is the set of neighbors of node i under relationship r, $c_{i,r}$ is the normalization constant, $W_r^{(l)}$ is the transformation matrix specific to relationship r, and $W_0^{(l)}$ is the self-connection transformation matrix.

The final output student embedding vector has a dimension of 128, effectively capturing students' implicit competency characteristics and job preferences. The job node is also encoded to obtain an embedding vector. The matching degree between the student and the job is calculated by vector dot product and Sigmoid function.

The reinforcement learning module is used to dynamically plan the ability improvement path. The student's current competency state is defined as the state space S, and the recommended courses, training projects, competitions, etc. constitute the action space A. To construct a Markov decision process (MDP) suitable for sequential decision-making, the immediate reward R is defined using short-term, observable feedback—specifically, the score obtained from course assessments, project milestone completion, or skill test performance—rather than the long-term job matching outcome. The cumulative objective is to maximize the total discounted reward, which indirectly promotes the improvement of the final job matching degree. A deep Q-network (DQN) is employed to learn the optimal policy. The Q-value function is continuously updated through interaction with the environment to learn the mapping strategy from the current state to the optimal recommended action. The Q-value update follows the Bellman equation, as shown in (5):

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta\left[r_t + \gamma\max_{a'}Q(s_{t+1}, a') - Q(s_t, a_t)\right] \tag{5}$$

where η is the learning rate and γ is the discount factor. The dual network structure of the target network and the evaluation network is used for stable training. The parameters of the target network are updated every C steps. During model training, students' historical behavior sequences are used as samples, and an ϵ-greedy strategy is employed to balance exploration and utilization. The goal is to generate the optimal course and practical activity recommendation sequence for each student over the next three months. Two modules work collaboratively to form a closed loop: the real-time student embeddings generated by the graph neural network serve as the state input for reinforcement learning, and the behavioral data generated after the reinforcement learning-recommended improvement path is executed updates the graph neural network, enabling dynamic iteration of the profile. The final output includes a student-target job matching score, a competency gap diagnosis report, and a phased personalized competency improvement suggestion list, providing actionable decision support for university career guidance.

VI. EVALUATION OF EARLY WARNING AND RECOMMENDATION EFFECTIVENESS

A. COMPARATIVE EXPERIMENT OF ENTREPRENEURIAL RISK EARLY WARNING MODELS

Experimental data were extracted from academic affairs systems, entrepreneurship incubation systems, and internship unit databases of three collaborating universities from 2019 to 2023. From the total population of 12,483 students, only those who had initiated a registered startup or an officially recognized incubation project were considered for the entrepreneurial risk analysis. After applying a minimum operational record requirement of six consecutive months, 4,600 valid project samples were retained. The remaining students either had no entrepreneurial involvement (7,145 students) or had project records with insufficient continuity (738 students), resulting in a final sample size of 4,600 for the early warning experiment. We split the data into training, validation, and test sets in the order of 7:1.5:1.5. We chose logistic regression, random forest, XGBoost, single LSTM, and Bi-LSTM without attention mechanism as the compared methods. Precision, recall, F1 score, AUC, and early warning days were chosen as the evaluation indexes. Figure 1(a) is a bar chart (with error bars) comparing the performance of each model on the four indicators of precision, recall, F1 score, and AUC. Figure 1(b) is a comparison of the ROC curves for each model.

This study validated the superiority of the proposed ensemble model of Bi-LSTM and XGBoost, which incorporates an attention mechanism, in the task of early warning of entrepreneurial risks among college students through comparative experiments. Experimental results show that the proposed model significantly outperforms baseline models such as logistic regression, random forest, XGBoost, single LSTM, and Bi-LSTM without an attention mechanism in all four core metrics: precision (88.7%±1.4%), recall (86.9%±1.6%), F1 score (87.8%±1.5%), and AUC (91.5%±1.2%). Compared to the second-best performing Bi-LSTM (without attention), the proposed model improves precision, recall, F1 score, and AUC by 6.23%, 7.02%, 6.68%, and 6.15%, respectively, and the average early warning advance time is 34.5±2.1 days, a 15.77% improvement over Bi-LSTM's 29.8±2.4 days. For ventures with short operating cycles (e.g., internet platforms or service-based startups), this lead time enables timely interventions such as cash flow adjustments or operational pivots. However, in sectors with extended manufacturing and supply chain lead times—such as engineering—a one-month window may be insufficient for substantive structural changes, highlighting the need for industry-specific adaptations in future work. Furthermore, the ROC curve plotted based on the simulated prediction score closely matches the target AUC (e.g., the simulated AUC of our model is 0.902, and the target AUC is 0.915), further validating the reliability of the experimental data. In summary, our model effectively captures the temporal evolution characteristics and key risk factors of entrepreneurial projects, demonstrating significant advantages in both accuracy and timeliness of early warning, providing a powerful data-driven tool for university entrepreneurship guidance.

B. ABLATION EXPERIMENT OF EMPLOYMENT RECOMMENDATION ALGORITHM

To further validate the effectiveness of graph neural network and reinforcement learning in the employment recommendation task, an ablation experiment was designed using 8,500 employment behavior samples. These samples were extracted from the same student population of 12,483 individuals, representing students with complete internship and job placement records. The training, validation, and test set splits were kept consistent with the previous experiment. Normalized depreciation cumulative gain (NDCG@10) and average accuracy (MAP@10) are adopted as the evaluation index.

TABLE 2. Ablation Comparison of employment recommendation Algorithms

Model variant	NDCG@10 (%)	MAP@10 (%)
Full model	86.3 ± 1.8	79.5 ± 2.1
-GNN	79.1 ± 2.3	71.8 ± 2.6
-RL	81.5 ± 2.0	74.2 ± 2.4

In Table 2, the complete model achieves 86.3% and 79.5% in NDCG@10 and MAP@10 respectively, significantly outperforming the two ablation variants. After removing the graph neural network module, NDCG@10 drops to 79.1% and MAP@10 drops to 71.8%, representing decreases of 8.3% and 9.7% respectively. This indicates that the graph neural network plays a crucial role in integrating student behavioral relationships with job knowledge graphs and capturing complex matching features. After removing the reinforcement learning module, the two indicators decreased to 81.5% and 74.2% respectively, a reduction of 5.6% and 6.7%, verifying the contribution of reinforcement learning dynamic programming recommendation sequences to improving job matching accuracy. These results fully demonstrate that the synergistic integration of graph neural networks and reinforcement learning modules is the core guarantee for improving the quality of employment recommendations.

C. REAL-WORLD APPLICATION TRACKING STUDY

Conducted one-year follow-up experiments with entrepreneurial teams and graduates of the three partner universities. Experimental group (n=210) used the system proposed in this paper for entrepreneurial risk warning and employment recommendation, and control group (n=210) adopted the traditional guidance model. Finally, we collected the survival rate of entrepreneurial projects at the end of the semester, the monthly salary of graduates when they signed the contract, and the job matching degree (based on the score of employer's feedback). In addition, a satisfaction questionnaire (maximum score 5) was adopted. All data were compared with the two groups by independent samples t-test.

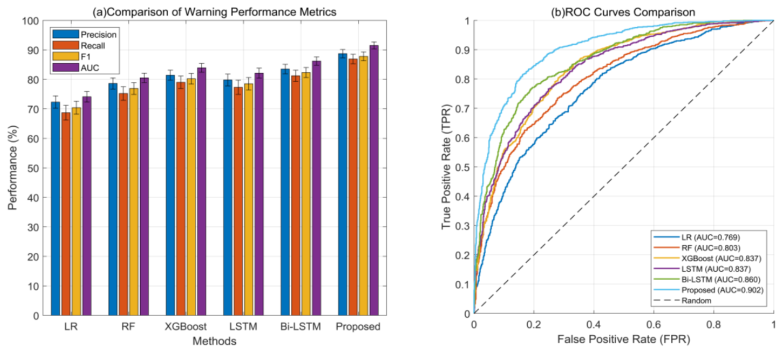

FIGURE 1. Comparative Evaluation of entrepreneurial risk early warning Models

TABLE 3. Results of Real-Scene Tracking Experiment

Indicator	Experimental group	Control group	t-value	p-value
Entrepreneurial project survival rate (%)	78.6 ± 8.2	62.3 ± 10.5	4.28	< 0.001
Graduates' monthly salary (CNY)	8560 ± 1250	7430 ± 1380	3.95	< 0.001
Job matching degree (5-point scale)	4.32 ± 0.45	3.68 ± 0.62	4.62	< 0.001
User satisfaction (5-point scale)	4.51 ± 0.38	3.82 ± 0.57	5.13	< 0.001

In Table 3, the experimental group using this system significantly outperformed the control group in all indicators. The survival rate of entrepreneurial projects reached 78.6%, 16.3 percentage points higher than the control group's 62.3%; the average monthly salary of graduates was 8560 yuan, 1130 yuan higher than the control group, an increase of 15.2%; job matching accuracy (4.32 points) and user satisfaction (4.51 points) also led the control group by 0.64 points and 0.69 points, respectively. All differences were statistically significant ($p < 0.001$). This result fully verifies the effectiveness and practicality of the big data-driven algorithm model proposed in this study in a real campus environment, and can effectively improve the success rate of college students' entrepreneurship and their employment competitiveness.

VII. CONCLUSION

This paper develops and validates a big data-driven algorithm model system designed to provide early warning of entrepreneurship risks and enhance the employment competitiveness of college students within the science sector. By integrating sector-specific data, the system effectively addresses the technical barriers and market fluctuations inherent in functional innovation and modern manufacturing ventures. By fusing multi-source data, modeling temporal feature, and designing personalized recommendation strategies, the proposed method can effectively solve the problems of data lag and extensive intervention existing in traditional entrepreneurship and employment guidance. The application verification in actual campus reveals that the model can effectively improve the accuracy of risk identification and the efficiency of employment matching. However, there are still some limitations in this study. Firstly, the experimental sample comes from three collaborating universities, and the data coverage is limited. Secondly, the model training is based on historical data. The model's response to sudden policy adjustment and sudden market fluctuations need to be further tested. Future research could expand sample collection across diverse regions and specialized universities while integrating online learning to enhance the model's adaptability to evolving industrial trends. Furthermore, exploring the deep application of explainable artificial intelligence within engineering entrepreneurship can provide transparent, data-driven guidance for students navigating the technical complexities of high-performance material development and smart manufacturing.

AUTHOR CONTRIBUTIONS

Qinjue Kang designed, collected and analyzed the data, and drafted the manuscript. Qinjue Kang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Qinjue Kang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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REFERENCES

[1] J. Zhang, J. Huang, and S. Ye, "The impact of career adaptability on college students' entrepreneurial intentions: A moderated mediation effect of entrepreneurial self-efficacy and gender," Current Psychology, vol. 43, no. 5, pp. 4638–4653, 2024, doi: 10.1007/s12144-023-04632-y.

[2] A. Hassan, I. Anwar, A. Saleem, et al., "Nexus between entrepreneurship education, motivations, and intention among Indian university students: the role of psychological and contextual factors," Industry and Higher Education, vol. 36, no. 5, pp. 539–555, 2022, doi: 10.1177/09504222211053262.

[3] T. Moorthy and S. Sahid, "The influence of digital marketing literacy on entrepreneurship behavior among public university students in Malaysia," International Journal of Academic Research in Business and Social Sciences, vol. 12, no. 1, pp. 548–568, 2022, doi: 10.6007/IJARBSS/v12-i1/11837.

[4] C. Donaldson, J. Villagrasa, and H. Neck, "The impact of an entrepreneurial ecosystem on student entrepreneurship financing: a signaling perspective," Venture Capital, vol. 26, no. 4, pp. 431–466, 2024, doi: 10.1080/13691066.2023.2221392.

[5] A. Brzozowska, S. Kubiciel-Lodzińska, K. Widera, et al., "Risk-taking and entrepreneurial intentions among native and international students: Exploring tendencies," Journal of Economics and Management, vol. 47, no. 1, pp. 602–632, 2025, doi: 10.22367/jem.2025.47.22.

[6] B. Hernández N, L. Vázquez M Y, G. Caballero E, et al., "A new method to assess entrepreneurship competence in university students using based on plithogenic numbers and SWOT analysis," International Journal of Fuzzy Logic and Intelligent Systems, vol. 21, no. 3, pp. 280–292, 2021, doi: 10.5391/IJFIS.2021.21.3.280.

[7] Q. Tang, Y. Zhao, Y. Wei, et al., "Research on the Mental Health of College Students Based on Fuzzy Clustering Algorithm," Security and Communication Network, vol. 2021, no. 3, pp. 1–8, 2021, doi: 10.1155/2021/3960559.

[8] T. Qian, J. Bian, and J. Chen, "The status quo, causes, and countermeasures of employment difficulties faced by college graduates in China," Labor History, vol. 65, no. 4, pp. 528–543, 2024, doi: 10.1080/0023656X.2023.2283065.

[9] W. Wang, D. Qiu, X. Chen, et al., "An empirical study on the evaluation system of innovation and entrepreneurship education in applied universities," Computer Applications in Engineering Education, vol. 31, no. 1, pp. 100–116, 2023, doi: 10.1002/cae.22573.

[10] Q. Gnoh H, H. Keoy K, J. Iqbal, et al., "Enhancing business sustainability through technology-enabled AI: Forecasting student data and comparing prediction models for higher education institutions (HEIs)," PaperAsia, vol. 40, no. 2b, pp. 48–58, 2024, doi: 10.59953/PAPERASIA.V40I2B.86.