Real-Time Assessment and Early Warning System for Industry-Education Integration in Higher Vocational Colleges Based on Multimodal Deep Learning

Yejun Xu
Office of Cooperation and Exchange, Suzhou Industrial Park Institute of Services Outsourcing, Suzhou 215123, Jiangsu, China
Corresponding author: Yejun Xu (e-mail: sisoxuyejun@163.com)

ABSTRACT The deepening of industry-education integration in higher vocational colleges requires more precise monitoring of vocational skill cultivation and industrial alignment. Existing assessments of industry-education integration mainly rely on static indicators and periodic surveys, making it difficult to achieve real-time perception and dynamic early warning. This study constructs a real-time assessment and early warning system for industry-education integration in higher vocational colleges based on multimodal deep learning. The system integrates three types of heterogeneous data: teaching behavior, industry cooperation, and management operation. Through the collaborative operation of a data fusion layer, dynamic graph learning layer, and early warning inference layer, it realizes quantitative assessment and hierarchical warning of industry-education integration status. The system is implemented in a higher vocational college in eastern China. Experimental results show that the system's comprehensive index is highly consistent with institutional assessment results, with a Pearson correlation coefficient of 0.87, and that its warning response time is much shorter than that of traditional assessment methods. The study provides an operable technical path for quality monitoring and decision support in vocational education.

INDEX TERMS multimodal deep learning, industry-education integration, real-time evaluation, early warning system, vocational education

I. INTRODUCTION

INDUSTRY-EDUCATION integration is one of the fundamental features of vocational education, and it determines the efficiency of talent cultivation in meeting industrial demands. In recent years, the national government has successively proposed many policies to promote the industry-education integration in vocational education from the institutional designing to the substantive operating. However, in the specific implementation process, there are still multiple challenges in quality monitoring in the integration of industry and education. On the one hand, the status of integration includes many dimensions such as the implementation of teaching, the participation of enterprises, the input of resources, and the development of students. Traditional evaluation methods, which primarily depend on annual reports and questionnaires, have low data collection frequency and long feedback cycles it is quite difficult to capture dynamic changes in the integration process in a timely manner. On the other hand, data is not united between different departments and systems; teaching management platforms, school-enterprise cooperation systems and internship records exist separately, without the mechanism of unified data integration and correlation analysis.

The development of multimodal deep learning has given the state assessment of complex systems a new technical approach. By using multiple types of data, including text, numerical data, images, and time series data, deep learning models are able to automatically extract features in high-dimensional space and create cross-modal correlation mappings. In fields like smart campuses and education quality monitoring, existing research has first proved that multimodal data is potential in the area of state identification and risk warning. However, under the special condition of industry education integration in vocational education, the existing studies have not established systematic real-time assessment framework and lack comprehensive technical solution that considers indicators on multidimensional indicators, update of dynamic and internal interpretive early warning. This study is mainly focused on the real-time assessment and early warning of the industry education integration situation in high vocational colleges, and builds a system based on multimodal deep learning. The system takes teaching behavior data, industry cooperation data and management operation data as inputs, and achieves the hierarchical assessment and risk warning of the industry-education integration status through data alignment, feature extraction, feature representation (fusion) and dynamic graph learning. The system design focuses on real-time performance and operability, which can make college administrators intervene immediately if there are anomalies in the integration quality.

II. RELATED WORK

The effectiveness of vocational education and industry-education integration is directly related to the quality of matching between the supply of skilled personnel and the demand of industries. Shukurullayevich [1] sorted out the application models of digital technology in vocational education, scientific research transformation and industrial collaboration, and analyzed practical cases. Putranto et al. [2] combined the vocational education practices of developing countries such as Indonesia to evaluate the actual effect of vocational education in improving employment matching. Ratnay et al. [3] systematically sorted out the application cases of the CIPP model in vocational education evaluation research and analyzed its advantages and limitations. McGrath and Ramsarup [4] used a combination of theoretical analysis and policy critique to review the relationship between vocational education and sustainable development goals and explore the role of vocational education and training in addressing global challenges. Kim et al. [5] evaluated the impact of lifelong vocational education on employment rate, salary level and job stability. Dahalan et al. [6] used a systematic literature review approach to focus on the application and effects of gamification in different vocational education scenarios. Toepper et al. [7] pointed out that the effect of knowledge transfer is affected by three factors: individual, teaching and context. The vocational education system needs to embed real work scenarios and continuous support mechanisms in the curriculum. Jalinus et al. [8] used instructional design and action research methods to develop and implement a series of teaching activities aimed at improving 4C competence and collected students' learning feedback and competence assessment data. Weijzen et al. [9] used narrative analysis and qualitative research methods to deeply analyze collaborative learning cases in vocational education and reveal the interaction and growth process of learners in practice. Rafiq et al. [10] introduced virtual reality technology into vocational education courses and evaluated students' participation and learning effects through questionnaire surveys and learning behavior analysis. This paper constructs a real-time assessment and early warning system for the integration of industry and education in higher vocational colleges based on multimodal deep learning. It aims to integrate multidimensional data such as teaching, industry, and management to achieve accurate characterization and dynamic monitoring of the integration of industry and education, thereby providing an operable digital path for quality governance and decision support in vocational education.

III. METHODS

A. MULTIMODAL DATA FUSION AND FEATURE EXTRACTION

The data foundation of the system comes from three types of heterogeneous data generated in the daily operation of higher vocational colleges. The first type is teaching behavior data, including student class attendance records, training platform operation logs, course assignment submission status, teacher teaching evaluation data, internship weekly report text content, etc. The second type is industry cooperation data, covering information on school-enterprise cooperation projects, records of enterprise mentors participating in teaching, number of enterprise internship positions provided, enterprise satisfaction feedback, and the implementation status of order class training agreements, etc. The third type is management and operation data, including records of professional settings and adjustments, frequency of use of training bases, progress of school-enterprise joint R&D projects, employment tracking survey data, and work ledgers of industry-education integration in secondary colleges, etc. [11].

On the data acquisition side, the system features a unified data access interface, supporting separate channels for structured data, semi-structured text, and time-series data. Structured data primarily includes numerical indicators and classification tags, such as the number of partner companies, internship duration, and attendance rate. Semi-structured text mainly originates from internship weekly reports, company feedback, and teaching summaries, requiring natural language processing to extract sentiment and key events. Time-series data covers the frequency of use of training equipment, student login behavior sequences, and the time sequence of company communication records.

In the feature extraction stage, the system adopts an appropriate encoding method for different modal data. For structured numerical data, after standardization and missing value imputation, it is input into a multilayer perceptron for feature mapping. For text data, a pre-trained lightweight language model is used to extract semantic embedding vectors, focusing on topics with high relevance to industry-education integration, such as job matching degree, enterprise guidance quality, and relevance of practical content. For time series data, a long short-term memory network is used to capture temporal dependencies and extract trend and periodic features. After the three types of features are independently encoded, they are weighted and fused through a self-attention mechanism. The weight allocation is determined by the dot-product similarity between modal embeddings, where the model dynamically prioritizes modes with higher information density. For instance, during internship peak periods, the attention mechanism assigns higher weights to industry cooperation data relative to campus teaching logs, ensuring the fusion feature vector remains sensitive to the most relevant indicators at any given time [12].

B. DYNAMIC GRAPH-BASED INDUSTRY-EDUCATION INTEGRATION STATUS MODELING

Industry-education integration is essentially a complex system involving multiple subjects and elements, and the static characteristics of a single time section are difficult to reflect the dynamic evolution characteristics of the integration process. To this end, the system introduces a dynamic graph neural network to model the industry-education integration network of higher vocational colleges as a heterogeneous graph that evolves over time. The nodes in the graph include different types of entities such as professional nodes, enterprise nodes, training base nodes, student group nodes, and teacher nodes. The edges represent the interaction relationships between entities, such as the cooperation edge between the professional and the enterprise, the usage edge between the student and the training base, and the project collaboration edge between the teacher and the enterprise [13-14].

The dynamic graph utilizes a dual-cycle update mechanism. While the comprehensive structural report is finalized on a monthly basis, the underlying graph embeddings and feature vectors are updated in near realtime (daily) using a sliding window approach. This ensures the system captures transient anomalies–such as sudden drops in training platform engagement–while maintaining the stability of the long-term integration network. Node features consist of the multimodal fusion feature vectors of associated node while edge weight is comprehensively calculated based on the interaction strength, cooperation duration, satisfaction rating etc. During the dynamic graph learning process, the system adopts the temporal graph convolutional network to learn the dynamic embedding representation of each node through the neighbor node information and crosstime step information transmission.

The comprehensive score for the industry-education integration is calculated on the basis of the results of dynamic graph embedding. The three basic dimensions of how the system evaluates are integration depth, integration breadth, and integration effectiveness. Integration depth shows the level of penetration of school-enterprise cooperation in talent cultivation, and is derived based on the aggregation of indicators such as course co-construction rate, proportion of enterprise mentor class hours, and number of dualsystem education projects. Integration breadth represents the professional scale and the strategic alignment of the cooperative enterprise network. It is calculated based on professional coverage and a weighted enterprise type entropy, which rewards diversity only when it aligns with the multidisciplinary requirements of the professional clusters, thereby distinguishing between strategic expansion and fragmented, low-quality cooperation. Integration effectiveness refers to the actual contribution of industry-education integration in the quality of talent cultivation, and these are manifested in indicators such as relevance rate of internship, graduate retention rate, and willingness of enterprise renewal. The scores of the three dimensions are obtained by means of the feature aggregation of corresponding subgraphs in the dynamic graph embedding and weighted for synthesis of a comprehensive industry education integration index.

C. EARLY WARNING MECHANISM AND ASSESSMENT OUTPUT

Based on dynamic evaluation, the system designed a three-layer progressive early warning mechanism to obtain a complete closed loop from the identification of status to intervention suggestions. The first layer is threshold early warning, which is the threshold division of the normal interval, attention interval and abnormal interval setting based on the historical distribution of industry-education integration comprehensive index. When the comprehensive index is included in the abnormal interval for two cycles of evaluation, the system will automatically trigger a first-level early warning sign to show a big deviation in the comprehensive integration status. The second layer is dimension early warning, which monitors the three sub-dimension integration depth, breadth and validity respectively. When a sub-dimension has a rapid decrease or is poorer than the benchmark value for an extended period of time, the system activates a second-level warning of the problem in advance and identifies the problem dimension. The third layer is node early warning, and it will detect the abnormal change of key nodes and key edges based on the results of dynamic graph embedding. For example, when the interaction intensity of a core cooperative enterprise node with other nodes decreases significantly, or the index of integration breadth of a professional node continues to decrease, the system will give a third-level early warning and output specific node information and change trends [15].

The output of the early warning is a combination of dashboards and reports. The desired system front-end allows for real-time updated comprehensive index curves for industry-education combination, dimensional scoring radar charts and dynamic evolution views. Administrators can click, and they can view the detailed assessment results and even early warning records at any point in time. For triggered early warning events, the system automatically generates early warning report including the early warning level, the trigger time, dimension, abnormal indicators, latest trend and preliminary intervention suggestions. Intervention suggestions are created based on a combination of historical case matching and professional cluster tagging. The system filters cases not only by logical similarity but also by disciplinary proximity (e.g., ensuring a manufacturing-based anomaly is matched with manufacturing-specific solutions). This mechanism accounts for qualitative differences in industry requirements, ensuring that improvement measures are contextually appropriate for different professional fields.

To prove the effectiveness of the method, the system was deployed and applied for one academic year in a vocational college in eastern China. To prevent data leakage during the training process, a time-series split method was strictly implemented, ensuring that data used for testing chronologically followed the training set. Furthermore, while this study focuses on a single institution, we applied a leave-one-major-out crossvalidation strategy to assess internal generalizability. Future research will incorporate multi-institutional data to mitigate the limitations of single-site validation and enhance the model's external robustness. This college is a national level pilot unit of industry-education integration, with a total of more than 12,000 students and more than 200 partner companies, has a relatively complete data foundation. During the period of deployment, the system effectively solved the problems of incrementally combining teaching behavior data, industry cooperation data and management operation data on a daily basis, and conducting monthly status assessment and early warning.

IV. RESULTS AND DISCUSSION

A. ANALYSIS OF THE ACCURACY AND TIMELINESS OF SYSTEM EVALUATION

In order to check the accuracy of the system's judgment of the status of industry-education integration, the research team used the annual assessment results related to industry-education integration actually conducted by the institutions as a standard. The annual assessment utilized independent qualitative rubrics and on-site expert evaluations conducted by the Quality Management Office, which are distinct from the raw digital logs used by our deep learning model. The Pearson correlation coefficient of 0.87 was calculated by comparing these expert-derived subjective scores against the system's automated objective index, suggesting that the model successfully mirrors human expert judgment without relying on the same input variables. A correlation analysis was carried out between the comprehensive index of the system at the end of the assessment period and the annual assessment score. The results revealed the Pearson correlation coefficient of 0.87, which implies that the degree of consistency is high between the results of assessment in the system and the conclusions of assessment in the institutions.

Further analysis was carried out on the performance of the system based on the identification of risks concerning the integration of industry-education. Eight majors that witnessed significant changes in the quality of cooperation or degeneration of integration during the past academic year were selected as positive examples, while 32 majors that did not witness significant changes in the quality were selected as negative examples. The capacity of the system to give effective preliminary warnings before anomalies occurred was studied. Early warning effectiveness was defined as the percentage of events for which the system had issued a warning of Level 2 or higher, one month or more ahead of the date of an anomaly occurrence. The identification performance using different warning time windows are presented in Table 1.

As shown in Table 1, the system demonstrates good foresight in identifying risks related to industry-education integration. One month before an anomaly occurred, the effective warning rate reached 87.5%, with only one major failing to trigger an effective warning. Retrospective analysis revealed that while the number of enterprise collaborations for this major was decreasing, the depth of collaboration remained at a high level in the short term, keeping the overall system score within the attention range. The effective warning rate two months in advance was 75.0%, and the effective warning rate three months in advance was 50.0%. This result indicates that the system has a strong ability to capture short- to medium-term risks, but there is still a possibility of missing earlier, weak signals.

Regarding the time timeliness of the assessment, a comparison was made between the real-time assessment method of the system and the traditional annual survey method. Under the traditional method, institutions perform assessments of industry-education integration on an annual basis using the questionnaire, interview, and submission of documents, and an average of 42 days are required from the time of data collection to the issuance of the report. The system completes a full assessment cycle in an average of 14.5 hours. This duration includes automated data cleaning, cross-departmental data synchronization (ETL), and model inference. Even with these preparatory stages included, the turnaround remains significantly more efficient than the 42-day traditional cycle, which is heavily delayed by manual data entry and human-led interviews. In terms of early warning response, the traditional way of doing things is to report and then verify after the anomaly is detected and it takes on average 18 days to report and verify. The system, however, immediately alerts the management terminals after triggering the alert, so the average response time is cut to 2.5 days.

B. DISTRIBUTION AND VARIATION CHARACTERISTICS OF EVALUATION RESULTS FOR EACH DIMENSION

The system completed 12 monthly assessments during its deployment period, covering changes in the industry-education integration status of the three secondary colleges. From the perspective of integration depth, the scores of each college showed significant fluctuations. Figure 1 shows the integration depth scores of the three representative colleges at the end of each of the four quarters.

The School of Intelligent Manufacturing's integration depth score peaked at 85.6 in Q2, then declined to 78.4 in Q3. Analysis of the raw data indicates this decline was primarily due to adjustments in production plans and a suspension of student internships by two core manufacturing companies. The system detected a weakening of interaction between enterprise and professional nodes at the beginning of Q3, triggering a Level 3 warning. The school promptly communicated and coordinated with the companies, resuming some collaborative projects in Q4, and the score rebounded to 81.2. The School of Information Technology showed a continuous upward trend in integration depth. In tandem with the newly introduced Integrated Circuit Industry College, the number of jointly developed courses increased from 4 in Q1 to 11 in Q4, and the number of

TABLE 1. Statistics on the Effectiveness of Industry-Education Integration Risk Warning

Warning time window	Number of positive examples	Number of effective early warnings	Effective early warning rate
1 month in advance	8	7	87.5%
2 months in advance	8	6	75.0%
3 months in advance	8	4	50.0%

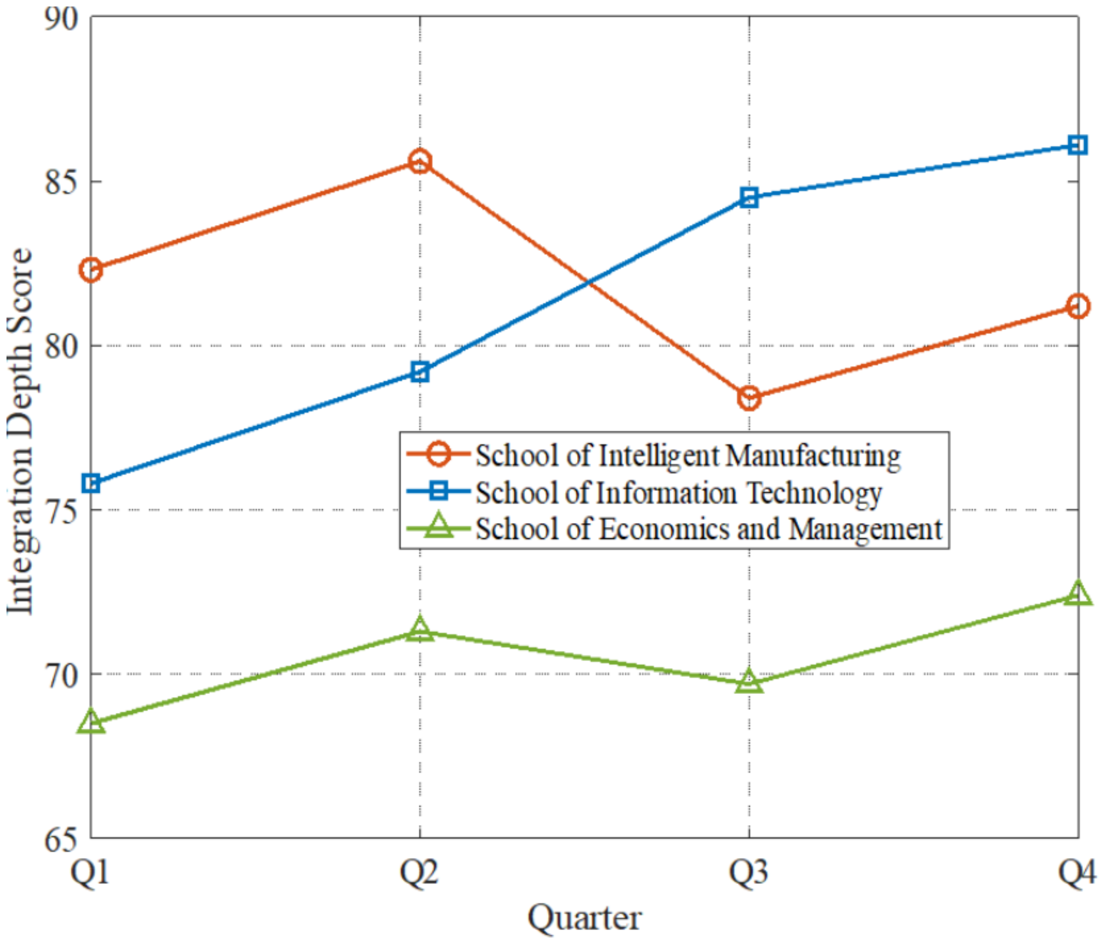

FIGURE 1. shows the quarterly scores of the integration depth of some secondary colleges

class hours involving enterprise mentors increased by 162%, supporting the steady improvement in the integration depth score. The School of Economics and Management's overall integration depth was low and growing slowly, mainly due to the fact that most of the partner companies in this professional group are small and mediumsized service enterprises with limited capacity to invest in course co-construction and dual-system education.

The assessment results for the breadth of integration show that the diversity of cooperative enterprise types across the university significantly improved in the third quarter. The system identified new enterprise nodes in fields such as new energy and intelligent connected vehicles, complementing the existing cooperative network which was mainly based on traditional manufacturing. Table 2 shows the differences in key indicators of integration effectiveness among various professional clusters.

Information technology-related majors performed best across all indicators, with an internship-to-job placement rate of 86.5%, a graduate retention rate of 81.2%, and a 91.2% willingness of employers to renew contracts. These majors have close partnerships with regional software parks and digital industry bases, resulting in stable employer demand and high job matching rates. Modern service-related majors had relatively lower indicators, with an internship-to-job placement rate of 72.3% and a graduate retention rate of 68.5%. Further analysis revealed a higher proportion of students in this major choosing to pursue further studies

TABLE 2. Comparison of Key Indicators of Integration Effectiveness of Various Professional Clusters

Professional Group	Internship matching rate	Graduation retention rate	Corporate renewal intentions
Intelligent Manufacturing Professional Group	84.2%	76.8%	89.5%
Information Technology Major Group	86.5%	81.2%	91.2%
Modern service-related professional groups	72.3%	68.5%	78.6%
Cultural and artistic professional groups	75.8%	71.4%	82.3%

after their internships, and some employers reported high intern turnover, impacting contract renewal intentions. The system detected that the integration validity index for this major was more than 15% below the university average for three consecutive months in the third quarter, triggering a level-two warning. The university subsequently conducted a special investigation and adjusted internship arrangements and further study support policies for this major.

C. APPLICATION EFFECT AND FEEDBACK OF THE EARLY WARNING SYSTEM

During systems deployment, a total of 47 warnings were triggered from different levels, which includes, 3 Level 1 warnings, 16 Level 2 warnings and 28-Level 3 warnings. These warning events covered six secondary colleges and various scenarios such as change in partner companies, reduced utilisation of training bases, changes in professional structures and student internship attrition. The follow-up handling of such warning events was tracked and the accuracy of the warnings and actual effectiveness of the interventions statistically analyzed. The precision of early warnings is based on the proportion of cases where there are occurrences where anomalies do indeed exist and require intervention after issuing an early warning. Level 1 warnings were issued 3 times, and in all the cases, the anomalies were confirmed, giving an accuracy rate of 100.0%. Level 2 warnings were issued 16 times with 14 verifying anomalies and 2 false alarms, an accuracy rate of 87.5%. Level 3 warnings were given 28 times, 21 of which confirmed anomalies and 7 were spontaneous recovery after short-term fluctuations, which is 75.0% accuracy. False alarms occurred prouduction, mostly at the level 3 warning, caused by reasons such as some companies temporarily reducing interaction during holidays and temporary data collection delays. The overall early warning accuracy rate was 80.9%, which means that although the system has good sensitivity, there remains some false alarm rate, which is further morale-boosting through the addition of more granular contextual information.

Regarding the intervention effect, 21 cases that set up the targeted improvement measures after the early warning were followed up to evaluate the recovery of the comprehensive index of industry-education integration. In 17 of these case, the comprehensive index rebounded to above the attention range within 2 evaluation periods after the intervention resulting in an effective intervention rate of 81.0%. Of the four cases that did not effectively recover, two involve termination of the cooperation caused by corporate strategic adjustments, one involves a reduction of professional enrollment resulting in a simultaneous reduction in the cooperation scale, and the other involves the tardy reaction caused by changes in college management personnel. The intervention effect shows that the early warning system of the system can give effective support to the management decision in most cases. However, for structural factors that lead to a decline in the quality of integration, the early warning system alone is not sufficient to modify the trend but it must be coupled with longer-term adjustments with regard to resource allocation and planning.

Feedback from university administrators on user experience with the system shows that the dynamic visualization function is providing an intuitive perspective on the evolution of the industry-education integration network that facilitates the ability to quickly identify the key nodes and weak links. The dimensional alert function facilitates differencing among problems (no vague attribution to administrator). Some of the administrators did comment that the system could be further refined in terms of the refinement of alert suggestions, currently the alert suggestions are based on rule matching, and in future the system could add more historical success stories and industry external information to refine and increase the specificity and operability of the suggestions. In summary, the real-time assessment and early warning system of industry education integration based on the multimodal deep learning model shows very good performance in terms of assessment accuracy, the timeliness of early warning and the effectiveness of the application. The system could integrate heterogeneous data together from several sources to characterize dynamically the situation of integration and proactively identify the risks, which can be a feasible technique to make a quality control of the process of industry-education integration in higher vocational colleges.

V. CONCLUSION

This study builds a real-time assessment and early warning system on the industry education integration status of higher vocational colleges based on the deep learning multi-modal system. Focusing on three types of data, namely teaching behavior, industry cooperation, and management operation, it designs three core modules, which are multimodal data fusion and feature extraction, dynamic graph state modeling, and threelevel early warning mechanism. This gives an operable technical solution, as well as empirical evidence, for the practice of monitoring the quality of the integration of industry and education in vocational education. There are limitations inherent in this particular study. The system deployment is limited to one higher vocational college and the data sources and model parameters are also college-specific, so that for expansion to other kinds of vocational colleges they need to be adapted and adjusted. The early warning suggestion module also based on the rule matching now, and its intelligence level needs improvement. The future research will expand to multiple colleges to develop a cross-college industry education integration assessment benchmark. Simultaneously, it will input outside industrial economic data and improve the ability of the system to perceive changes in the macro-environment, which will also improve the accuracy and foresight of the early warning system.

AUTHOR CONTRIBUTIONS

Yejun Xu designed, collected and analyzed the data, and drafted the manuscript. Yejun Xu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Yejun Xu 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.

FUNDING

This research was supported by,

Research Topic: Development of Elevator System for Intelligent Environmental Control Cleaning Robots BY20250621

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] U. S. Shukurullayevich, “Digital Technologies as a Driver of Integration Between Education, Science and Industry, ” Central Asian Journal of Innovations on Tourism Management and Finance, vol. 7, no. 2, pp. 265-274, 2026, doi: 10.51699/cajitmf.v7i2.1206.

[2] F. X. G. F. Putranto, C. Natalia, and N. K. D. Pitriyani, “Closing the Gap Between Education and Labor Market Requirement: Do Vocational Education Matter?” The Journal of Indonesia Sustainable Development Planning, vol. 5, no. 3, pp. 181-191, 2024, doi: 10.46456/jisdep.v5i3.614.

[3] G. Ratnay, R. Indriaswuri, D. G. C. Widayanthi, et al., “CIPP Evaluation Model for Vocational Education: A Critical Review, ” Education Quarterly Reviews, vol. 5, no. 3, pp. 1-8, 2022, doi: 10.31014/aior.1993.05.03.519.

[4] S. McGrath and P. Ramsarup, “Towards vocational education and training and skills development for sustainable futures, ” Journal of Vocational Education & Training, vol. 76, no. 2, pp. 247-258, 2024, doi: 10.1080/13636820.2024.2317574.

[5] J. Y. J. Kim, E. B. Kim, and D. H. Lim, “A meta-analysis of the effects of lifelong vocational education in South Korea, ” European Journal of Training and Development, vol. 48, no. 7-8, pp. 749-765, 2024, doi: 10.1108/EJTD-02-2023-0026.

[6] F. Dahalan, N. Alias, and M. S. N. Shaharom, “Gamification and game based learning for vocational education and training: A systematic literature review, ” Education and Information Technologies, vol. 29, no. 2, pp. 1279-1317, 2024, doi: 10.1007/s10639-022-11548-w.

[7] M. Toepper, O. Zlatkin-Troitschanskaia, and C. Kühling-Thees, “Literature review of international empirical research on transfer of vocational education and training, ” International Journal of Training and Development, vol. 26, no. 4, pp. 686-708, 2022, doi: 10.1111/ijtd.12276.

[8] N. Jalinus, S. Sukardi, R. E. Wulansari, et al., “Teaching activities for supporting students’ 4cs skills development in vocational education, ” Journal of Engineering Researcher and Lecturer, vol. 2, no. 2, pp. 70-79, 2023, doi: 10.58712/jerel.v2i2.95.

[9] S. M. G. Weijzen, C. Onck, A. E. Wals, et al., “Vocational education for a sustainable future: Unveiling the collaborative learning narratives to make space for learning, ” Journal of Vocational Education & Training, vol. 76, no. 2, pp. 331-353, 2024, doi: 10.1080/13636820.2023.2270468.

[10] A. A. Rafiq, M. B. Triyono, and I. W. Djatmiko, “Enhancing student engagement in vocational education by using virtual reality, ” Waikato Journal of Education, vol. 27, no. 3, pp. 175-188, 2022, doi: 10.15663/wje.v27i3.964.

[11] V. Kovalchuk, S. V. Maslich, N. M. Tkachenko, et al., “Vocational education in the context of modern problems and challenges, ” Journal of Curriculum and Teaching, vol. 11, no. 8, pp. 329-338, 2022, doi: 10.5430/jct.v11n8p329.

[12] R. R. Ravichandran and J. Mahapatra, “Virtual reality in vocational education and training: challenges and possibilities, ” Journal of Digital Learning and Education, vol. 3, no. 1, pp. 25-31, 2023, doi: 10.52562/jdle.v3i1.602.

[13] J. Klassen, “International organisations in vocational education and training: a literature review, ” Journal of Vocational Education & Training, vol. 77, no. 3, pp. 792-818, 2025, doi: 10.1080/13636820.2024.2320895.

[14] V. I. Kovalchuk, S. V. Maslich, and L. H. Movchan, “Digitalization of vocational education under crisis conditions, ” Educational Technology Quarterly, vol. 2023, no. 1, pp. 1-17, 2023, doi: 10.55056/etq.49.

[15] S. F. Fam, X. E. Lan, S. I. Wahjono, et al., “Bibliometric Analysis on Technical and Vocational Education and Training (TVET) Research, ” International Journal of Academic Research in Progressive Education and Development, vol. 13, no. 3, pp. 2528-2547, 2024, doi: 10.6007/IJARPED/v13-i3/22260.