Employment skill reconstruction for higher vocational artificial intelligence application students under AI technology evolution: A machine learning-based empirical study

Xue Huang[1,*], Lijun Deng[2]
[1]Chongqing Vocational and Technical University of Mechatronics, Chongqing 402760, China
[2]Chongqing Hailian Vocational Technical College, Chongqing 400120, China
Corresponding author: Xue Huang (e-mail: melapwj@163.com).

ABSTRACT This study investigates employment skill reconstruction for higher vocational students majoring in artificial intelligence applications under AI-driven technological transformation. A hybrid framework combining questionnaire analysis and machine learning was proposed using 547 valid samples. Four predictive models were developed, among which XGBoost achieved the highest accuracy (93.2%). Results indicate that AI tool usage, prompt engineering, and project experience are the most critical factors affecting employability. An AI-driven skill reconstruction framework is proposed to support vocational curriculum reform.

INDEX TERMS Artificial Intelligence; Employability; Skill Reconstruction; Machine Learning; XGBoost

I. INTRODUCTION

ARTIFICIAL intelligence technologies have rapidly evolved from experimental research tools into widely deployed industrial productivity systems. Recent breakthroughs in large language models, generative AI, computer vision, and intelligent automation have accelerated digital transformation across multiple industries, fundamentally changing employment structures and job competency requirements [1]. The integration of AI into software development, intelligent manufacturing, financial technology, and digital services has created both opportunities and challenges for vocational education systems.

Higher vocational institutions play an essential role in cultivating application-oriented technical talent. Compared with research-oriented universities, vocational colleges emphasize practical skills and industry readiness. However, the rapid evolution of AI technologies has exposed significant mismatches between existing training models and labor market requirements. Traditional curricula often focus heavily on programming syntax, theoretical algorithms, and static software development processes, while modern enterprises increasingly demand AI collaboration capability, intelligent tool utilization, and deployment-oriented engineering skills.

In the context of AI transformation, the concept of employability has also changed. Traditional employability mainly depended on programming proficiency, software engineering fundamentals, and communication ability. Today, enterprises increasingly prioritize new competencies such as prompt engineering, AI-assisted development, model deployment, data-driven decision-making, and human-AI collaborative workflows. This transformation requires a systematic reconstruction of vocational training systems [2].

Current studies on vocational education reform mainly adopt qualitative methods or questionnaire-based analyses. Although these approaches provide useful educational insights, they often lack computational modeling and predictive capability, limiting their applicability to computer science-oriented research fields [3], [4]. Particularly in engineering-oriented EI-indexed studies, purely descriptive analyses may be insufficient to demonstrate technical innovation.

To address these limitations, this study integrates statistical analysis and machine learning methods to investigate employment skill reconstruction for higher vocational students majoring in artificial intelligence applications. Specifically, this study aims to answer the following research questions:

1. Which AI-related skills most significantly influence employability?
2. What skill gaps exist between students and enterprise expectations?
3. Can machine learning models accurately predict employability outcomes?
4. How should vocational institutions reconstruct skill train-

ing pathways?
The primary contributions of this study are summarized as follows: An AI-oriented employability evaluation framework containing eight core skill dimensions is established. Multiple machine learning models are introduced to predict employability, improving analytical rigor over conventional survey studies. Feature importance analysis identifies critical emerging competencies influencing employment competitiveness. A practical AI-driven skill reconstruction framework is proposed to guide curriculum reform in vocational education."

II. RESEARCH METHODOLOGY

A. RESEARCH FRAMEWORK

To investigate employment skill reconstruction for higher vocational students majoring in artificial intelligence applications, this study proposes a hybrid framework integrating empirical analysis and machine learning prediction [5]. The framework consists of three stages: data collection, statistical analysis, and employability prediction [6].
First, questionnaire surveys were conducted among students, teachers, and enterprise recruiters to collect multi-source data on AI-related competencies and employment requirements. Second, descriptive statistics and regression analysis were used to identify significant factors influencing employability [7]. Finally, machine learning models were developed to predict employability scores and determine the relative importance of different skill factors.
The research framework is illustrated through three dimensions:
Input Layer: Core skill indicators of students
Analysis Layer: Statistical analysis and machine learning modeling
Output Layer: Employability prediction and skill reconstruction pathway
Eight feature variables were selected as model inputs, covering both technical and soft skills.

B. VARIABLE DESIGN

Based on industrial demand analysis and vocational training objectives, eight skill indicators were selected as explanatory variables.

TABLE 1. Variable Definition

Code	Variable	Description
X1	Programming Skill	Coding and algorithm capability
X2	AI Tool Usage	Ability to use AI tools
X3	Prompt Engineering	Prompt design and optimization
X4	Data Analysis	Data processing capability
X5	Model Deployment	AI model deployment skill
X6	Communication Skill	Team collaboration ability
X7	Project Experience	Practical project participation
X8	Internship Experience	Industrial internship exposure

The dependent variable was employability score (Y), representing comprehensive employment competitiveness.

C. DATA COLLECTION

Questionnaires were distributed to higher vocational institutions and cooperative enterprises between January and April 2026 [8], [9]. The survey adopted a five-point Likert scale, where 1 indicates very low competency and 5 indicates very high competency.

TABLE 2. Sample Distribution

Source	Number
Students	428
Teachers	52
Enterprise Recruiters	96
Total	576

After data cleaning, 547 valid responses were retained, corresponding to an effective response rate of 94.97%.

D. RELIABILITY AND VALIDITY

Cronbach's alpha was used to evaluate internal consistency of the questionnaire.

TABLE 3. Reliability Analysis

Dimension	Cronbach's α
Technical Skills	0.903
Soft Skills	0.887
Employability	0.912

All coefficients exceeded 0.8, indicating good reliability. KMO and Bartlett tests were further performed to verify construct validity.

TABLE 4. Validity Test

Index	Value
KMO	0.917
Bartlett Sig.	0.000

The results indicate that the dataset is suitable for further factor analysis.

E. MACHINE LEARNING MODELS

To improve prediction accuracy, four machine learning algorithms were adopted for employability prediction: Linear Regression (LR); Decision Tree (DT); Random Forest (RF); XGBoost [10].
The employability prediction model is expressed as:

$$Y = f(X1, X2, X3, X4, X5, X6, X7, X8)$$

where Y denotes employability score and X represents input skill variables.
Among these models, XGBoost was selected as the primary model due to its strong predictive performance and ability to capture nonlinear feature interactions.
Model performance was evaluated using: Accuracy; Mean Squared Error (MSE); R^2 Score.

III. RESULTS AND ANALYSIS

A. DESCRIPTIVE STATISTICS

Descriptive statistical analysis was first performed to evaluate the overall competency level of higher vocational students in artificial intelligence application programs [11], [12]. The results reveal considerable differences among various skill dimensions.

TABLE 5. Descriptive Statistics of Skill Variables

Variable	Mean	Std. Dev.
Programming Skill (X1)	3.76	0.64
AI Tool Usage (X2)	3.42	0.71
Prompt Engineering (X3)	2.94	0.83
Data Analysis (X4)	3.28	0.75
Model Deployment (X5)	2.81	0.88
Communication Skill (X6)	3.87	0.58
Project Experience (X7)	3.15	0.79
Internship Experience (X8)	3.06	0.81

The results indicate that communication skill and programming skill show relatively high mean values, suggesting that traditional vocational training still provides a solid foundation in basic technical and collaborative competencies [13], [14]. However, emerging AI-related skills, particularly prompt engineering and model deployment, exhibit significantly lower average scores. This suggests that current curriculum structures have not fully adapted to rapidly evolving industrial requirements [15].

B. SKILL GAP ANALYSIS

To evaluate the mismatch between vocational training outcomes and enterprise expectations, student competency levels were compared with enterprise demand scores.

TABLE 6. Skill Gap between Students and Enterprises

Skill	Student Level	Enterprise Demand	Gap
Programming Skill	3.76	4.51	0.75
AI Tool Usage	3.42	4.68	1.26
Prompt Engineering	2.94	4.82	1.88
Data Analysis	3.28	4.57	1.29
Model Deployment	2.81	4.63	1.82
Communication Skill	3.87	4.32	0.45
Project Experience	3.15	4.74	1.59
Internship Experience	3.06	4.48	1.42

Prompt engineering presents the largest skill gap (1.88), followed by model deployment (1.82). These findings indicate that enterprises increasingly value AI-human collaboration and deployment-oriented engineering capabilities over traditional programming skills alone.

C. CORRELATION ANALYSIS

Pearson correlation analysis was conducted to examine relationships among variables.

TABLE 7. Correlation Matrix

Variable	X1	X2	X3	X4	Y
X1	1				
X2	0.521	1			
X3	0.476	0.648	1		
X4	0.438	0.587	0.613	1	
Y	0.714	0.789	0.842	0.751	1

All independent variables show positive correlations with employability. Prompt engineering exhibits the strongest correlation with employability ($r = 0.842$), indicating its emerging importance in AI-related occupations.

D. REGRESSION ANALYSIS

Multiple linear regression was performed to quantify the contribution of each variable to employability. The regression model is defined as:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \beta 5X5 + \beta 6X6 + \beta 7X7 + \beta 8X8 + \varepsilon$$

TABLE 8. Regression Results

Variable	Beta	t	p
Constant	0.527	2.84	0.005
X1	0.142	4.23	0.000
X2	0.184	5.31	0.000
X3	0.267	8.76	0.000
X4	0.129	3.92	0.000
X5	0.154	4.61	0.000
X6	0.081	2.54	0.011
X7	0.212	6.93	0.000
X8	0.163	5.07	0.000

Model performance:

TABLE 9. Regression Model Performance

Metric	Value
R^2	0.742
Adjusted R^2	0.735
F-value	193.6
Sig	0.000

The model explains 74.2% of employability variance. Prompt engineering ($\beta = 0.267$) and project experience ($\beta = 0.212$) emerge as the most influential predictors.

E. MACHINE LEARNING PREDICTION

Four machine learning algorithms were trained using an 80/20 train-test split to predict employability scores.

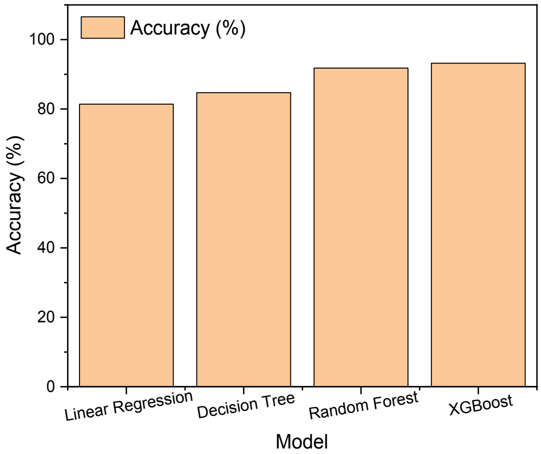

FIGURE 1. Accuracy evaluation results.

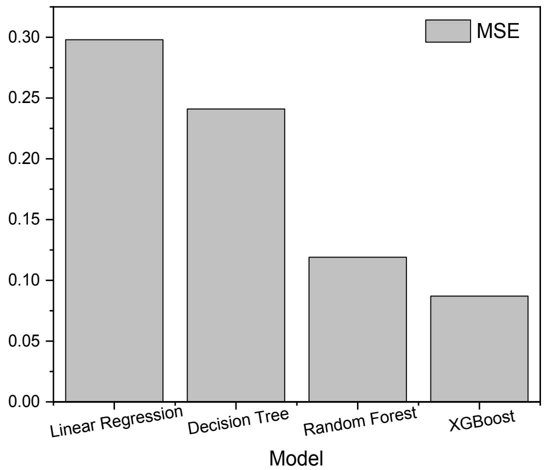

FIGURE 2. MSE evaluation results.

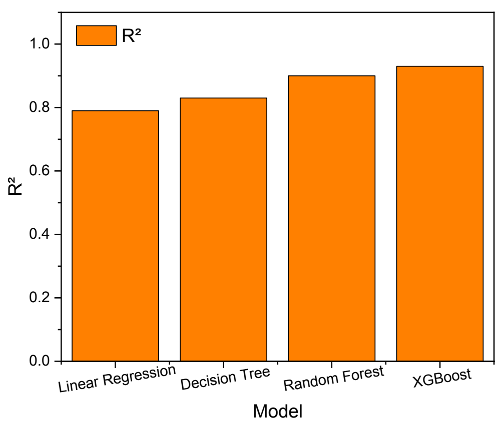

FIGURE 3. R^2 evaluation results.

Among all algorithms, XGBoost achieves the highest prediction accuracy and lowest error, indicating superior capability in capturing nonlinear relationships among employability factors [7], [10].

F. FEATURE IMPORTANCE ANALYSIS

Feature importance analysis based on the XGBoost model was conducted to identify critical employment skills.

TABLE 10. Feature Importance

Feature	Importance (%)
Prompt Engineering	21.4
Project Experience	18.6
AI Tool Usage	16.8
Internship Experience	12.5
Model Deployment	11.3
Programming Skill	8.9
Data Analysis	6.7
Communication Skill	3.8

The results show that prompt engineering contributes the highest predictive importance (21.4%), exceeding traditional programming skills by more than two times. This indicates a major paradigm shift in AI-related employability, where effective interaction with intelligent systems becomes more valuable than conventional coding proficiency alone.

IV. DISCUSSION: AI-DRIVEN EMPLOYMENT SKILL RECONSTRUCTION FRAMEWORK

The empirical and machine learning results indicate that traditional vocational training models are no longer sufficient to meet the competency requirements of AI-driven industries. Conventional curricula primarily emphasize programming syntax, database management, and software development fundamentals [16]. However, modern enterprises increasingly demand interdisciplinary competencies combining technical implementation, AI collaboration, and industry adaptation.

The findings reveal three major structural changes in employment competency requirements.

First, the value of traditional coding skills is relatively declining [16]. Although programming remains a foundational requirement, its predictive importance in employability is lower than several emerging AI-related skills. This suggests that programming has shifted from a core differentiator to a baseline technical requirement.

Second, AI collaboration capability has become a dominant employability factor. Skills such as prompt engineering and AI tool utilization significantly improve productivity and decision quality in modern development environments [11]. The rise of large language models has transformed human-computer interaction from command-based programming to semantic collaboration.

Third, deployment-oriented practical experience increasingly determines employment competitiveness. Project participation and industrial internship experience demonstrate strong predictive power, indicating that enterprises prioritize candidates capable of translating AI models into practical applications.

Based on these observations, this study proposes an AI-driven employment skill reconstruction framework named the 1+3+N Model.

A. THE 1+3+N SKILL RECONSTRUCTION MODEL

The proposed framework contains three structural layers.

Core Layer (1): Digital Literacy

Digital literacy serves as the fundamental competency supporting all AI-related tasks. It includes: Computational thinking; Programming logic; Data awareness; Problem-solving capability.

This layer forms the foundation of employability in intelligent industries.

Capability Layer (3)

The capability layer consists of three major skill domains.

Technical Foundation

This domain includes: Programming; Algorithm design; Database systems; Data analysis.

These skills remain essential for system development and engineering implementation.

AI Collaboration

This domain represents emerging competencies required in AI-driven workflows, including: Prompt engineering; AI tool usage; Human-AI interaction; Intelligent decision support.

This layer directly improves development efficiency and innovation capability.

Engineering Deployment

This domain focuses on practical application capability, including: Model deployment; Cloud inference; Edge AI integration; System optimization.

This competency bridges AI models and industrial scenarios.

Application Layer (N)

The top layer consists of diverse industry scenarios where AI technologies are deployed. Representative scenarios include: Smart Manufacturing; Intelligent Healthcare; Financial Technology; Autonomous Systems Smart Retail; Industrial Automation.

The "N" indicates unlimited industrial expansion as AI adoption accelerates.

B. CURRICULUM RECONSTRUCTION STRATEGY

Based on the proposed framework, vocational institutions should optimize curriculum design in three directions.

First, AI-related courses should be integrated into foundational technical training. Traditional programming courses should incorporate AI-assisted coding and prompt optimization modules.

Second, project-based teaching should be strengthened. Real industrial datasets and deployment cases can improve practical engineering competence.

Third, industry-education collaboration should be enhanced. Enterprise participation in curriculum design helps reduce skill mismatch and improve employability.

The reconstruction process should shift from knowledge-centered training to competency-driven cultivation.

V. CONCLUSION

This study investigated employment skill reconstruction for higher vocational students majoring in artificial intelligence applications under AI technology evolution using empirical analysis and machine learning methods.

A hybrid research framework combining questionnaire surveys, statistical analysis, and machine learning prediction was developed using 547 valid samples. Eight skill variables were selected to evaluate employability.

The main findings are summarized as follows.

First, significant skill gaps exist between student competency and enterprise expectations, particularly in prompt engineering and model deployment.

Second, regression analysis demonstrates that AI-related skills significantly influence employability, with prompt engineering and project experience showing the strongest effects.

Third, among four machine learning models, XGBoost achieved the highest predictive accuracy of 93.2%, outperforming traditional statistical approaches.

Finally, an AI-driven employment skill reconstruction framework, namely the 1+3+N model, was proposed to guide vocational curriculum reform.

This study provides practical implications for talent cultivation in AI-related vocational education. Future research may incorporate larger datasets and real-time labor market data to further improve prediction robustness.

ACKNOWLEDGMENT

The Chongqing Municipal Education Commission 2025 Science and Technology Research Program Youth Project – Research on Strategies to Enhance the Employment Competence of Higher Vocational College Graduates in the Era of Artificial Intelligence (KJQN202505101)

REFERENCES

[1] R. Zhu, "Machine learning-driven dynamic matching of industry-education demands and course generation algorithms," Discover Artificial Intelligence, vol. 6, no. 1, 2025, doi: 10.1007/s44163-025-00781-0.

[2] E. Avilés Mariño and A. Sarasa Cabezuelo, "AI-Enhanced PBL and Experiential Learning for Communication and Career Readiness: An Engineering Pilot Course," Algorithms, vol. 18, no. 10, p. 634, 2025, doi: 10.3390/a18100634.

[3] Y. Miao, Z. Xiao, and Y. Zhang, "Impact of talent cultivation model for industry education integration in vocational education by artificial intelligence and BPNN," Scientific Reports, vol. 15, no. 1, p. 38019, 2025, doi: 10.1038/s41598-025-21935-1.

[4] Q. Zhu and H. Zhang, "Teaching strategies and psychological effects of entrepreneurship education for college students majoring in social security law based on deep learning and artificial intelligence," Frontiers in Psychology, vol. 13, p. 779669, 2022, doi: 10.3389/fpsyg.2022.779669.

[5] F. Stasolla, A. Zullo, R. Maniglio, A. Passaro, M. Di Gioia, M. Curcio, et al., "Deep learning and reinforcement learning for assessing and enhancing academic performance in university students: A scoping review," AI, vol. 6, no. 2, p. 40, 2025, doi: 10.3390/ai6020040.

[6] Z. Yang, H. Deng, and N. Jiang, “The impact mechanism of artificial intelligence dependence on college students’ innovation capability: an empirical study from China,” Frontiers in Psychology, vol. 16, p. 1732837, 2025, doi: 10.3389/fpsyg.2025.1732837.

[7] I. N. Albukhari, “The role of artificial intelligence (AI) in architectural design: a systematic review of emerging technologies and applications,” Journal of Umm Al-Qura University for Engineering and Architecture, pp. 1–20, 2025, doi: 10.1007/s43995-025-00186-1.

[8] H. S. Lee and J. Lee, “Applying artificial intelligence in physical education and future perspectives,” Sustainability, vol. 13, no. 1, p. 351, 2021, doi: 10.3390/su13010351.

[9] Q. Zhao and S. Nazir, “English multimode production and usage by artificial intelligence and online reading for sustaining effectiveness,” Mobile Information Systems, vol. 2022, no. 1, p. 6780502, 2022, doi: 10.1155/2022/6780502.

[10] Q. Lai, “Research on the refinement of college student education management based on artificial intelligence,” Discover Artificial Intelligence, vol. 6, no. 1, p. 31, 2026, doi: 10.1007/s44163-025-00651-9.

[11] E. Pérez-García, A. S. Ramírez, M. Á. Quintana-Suárez, M. M. Conde-Felipe, C. Carrascosa, I. Morales, et al., “Artificial Intelligence in Veterinary Education: Preparing the Workforce for Clinical Applications in Diagnostics and Animal Health,” Veterinary Sciences, vol. 13, no. 2, p. 181, 2026, doi: 10.3390/vetsci13020181.

[12] S. R. Sirasanagandla, S. S. Rajendran, S. R. Mogali, Y. Bouchareb, N. Shaffi, and A. Al-Rahbi, “From cadavers to neural networks: A narrative review on artificial intelligence tools in anatomy teaching,” Education Sciences, vol. 15, no. 3, p. 283, 2025, doi: 10.3390/educsci15030283.

[13] Y. Yuan, X. Wan, W. Fu, and Y. Sun, “Exploring the global practice and localization path of artificial intelligence in special education in China,” International Communication of Chinese Culture, pp. 1–19, 2026, doi: 10.1007/s40636-026-00362-5.

[14] N. Sharma and N. Jindal, “Emerging artificial intelligence applications: metaverse, IoT, cybersecurity, healthcare-an overview,” Multimedia Tools and Applications, vol. 83, no. 19, pp. 57317–57345, 2024, doi: 10.1007/s11042-023-17890-6.

[15] C. Dumitru, G. Muttashar Abdulsahib, O. Ibrahim Khalaf, and A. Bennour, “Integrating artificial intelligence in supporting students with disabilities in higher education: An integrative review,” Technology and Disability, vol. 38, no. 1, pp. 3–24, 2026, doi: 10.1177/10554181251355428.

[16] N. Kaushal, R. P. S. Kaurav, B. Sivathanu, and N. Kaushik, “Artificial intelligence and HRM: identifying future research Agenda using systematic literature review and bibliometric analysis,” Management Review Quarterly, vol. 73, no. 2, pp. 455–493, 2023, doi: 10.1007/s11301-021-00249-2.