Industry 5.0 and Education 5.0: Transforming Vocational Education through Intelligent Technology

Hongli Zhang [1,2], Wai Yie Leong[1*]

[1]Faculty of Engineering and Quantity Surveying, INTI International University, Malaysia
[2]Department of Information Engineering, Heilongjiang Institute of Construction Technology, China

***Email:** i24026601@student.newinti.edu.my, waiyie.leong@newinti.edu.my

Abstract

As new directions of development, Industry 5.0 and Education 5.0 emphasize human-machine collaboration, personalized services, and the application of intelligent technologies. This paper aims to explore how intelligent technology can transform vocational education to enhance the effectiveness of vocational training and meet the demands of the modern economy. By analyzing the research gaps in personalized learning paths, emotion-driven learning, cross-disciplinary integration, and long-term learning behavior analysis, the paper proposes four improved algorithms: the adaptive learning path generation algorithm, the emotion-driven personalized learning algorithm, the cross-disciplinary knowledge graph algorithm, and the long-term learning behavior prediction algorithm. The research demonstrates that these innovative approaches effectively address the limitations of current personalized learning systems, providing theoretical and practical support for the intelligent transformation of vocational education.

Keywords

Industry 5.0, Education 5.0, Intelligent Technology, Vocational Education, Personalized Learning

Introduction

Industry 5.0 marks a new phase in the collaboration between intelligent technology and humans, not only focusing on automation and intelligence but also emphasizing technology's role in serving human needs for personalization (Aheleroff et al., 2022). Correspondingly, Education 5.0 introduces the concept of personalized education based on artificial intelligence and big data, especially in the field of vocational education, where the application of intelligent technologies is set to transform traditional teaching models, making learning more efficient and customized (Song, 2022).However, the current personalized learning systems in vocational education still face several shortcomings, including insufficient dynamic adjustment of learning paths, limited integration of emotion recognition with the learning process, inadequate

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support for cross-disciplinary learning, and a lack of tracking and prediction of long-term learning behaviors (Leong, 2019; Ng, 2014). By proposing innovative algorithms and technological solutions, this paper seeks to address these gaps and promote the intelligent development of vocational education in the context of Industry 5.0 and Education 5.0 (Babu, 2024).

Existing Research Gaps: Personalized learning systems typically generate initial learning paths at the beginning of the learning process, lacking the ability to dynamically adjust according to the evolving needs of learners. Additionally, intelligent systems in vocational education mainly focus on learning outcomes and behavioral data, overlooking the influence of emotional states on learning effectiveness. Furthermore, these systems are often confined to single disciplines, lacking support for cross-disciplinary knowledge integration. Existing systems also tend to prioritize short-term learning outcomes, without adequately considering the evolution of long-term learning behaviors and their impact on vocational skill development.

Methodology

To address the issues of dynamic adaptation, emotional support, cross-disciplinary learning, and long-term planning in personalized vocational education, this paper designs four improved algorithms. Each algorithm was evaluated through experiments, combining data collection and analysis to verify its effectiveness in vocational education(Leong, 2024a).

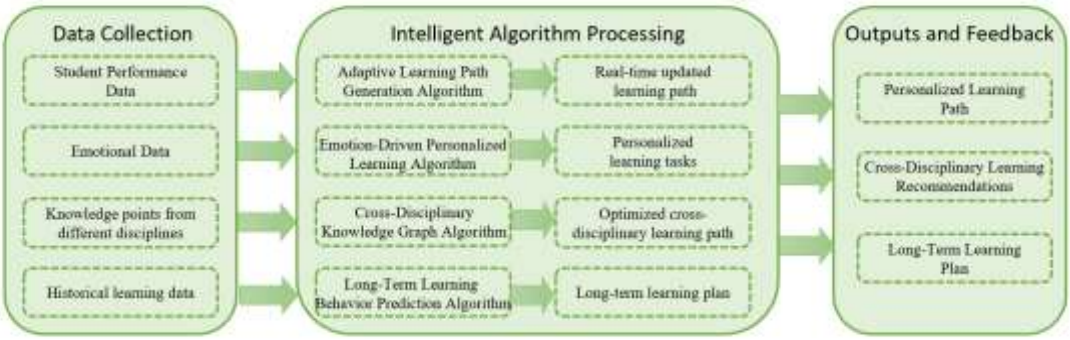


Figure 1. Workflow of Intelligent Technology Methodology for Personalized Learning in Vocational Education

A. Research Subjects and Experimental Design

This study selected 100 students from a vocational college, covering various vocational fields (e.g., mechanical engineering, information technology, and nursing). These students were randomly divided into an experimental group and a control group. The experimental group used an intelligent personalized learning system, while the control group used a traditional online learning platform. The experiment lasted six months, with tests conducted every two weeks and regular questionnaires to assess students' learning engagement and satisfaction.

B. Data Collection

Data were collected through a Learning Management System (LMS), covering students' academic performance, task completion, emotional states, cross-disciplinary learning performance, and long-term learning behaviors. Additionally, emotional data were collected using an emotion recognition. Survey questionnaires were used to gather data on learning satisfaction and engagement to more comprehensively evaluate the system's effectiveness (Carayannis & Morawska, 2023).

C. Adaptive Learning Path Generation Algorithm

The proposed adaptive learning path generation algorithm is based on reinforcement learning and can dynamically adjust the learning path according to the student's performance (Leong, 2022).The adaptive learning path generation algorithm is based on the Q-learning algorithm, and its core formula is as follows:

$$Q(s,a) = Q(s,a) + \alpha(r + \gamma max_{a'}Q(s',a') - Q(s,a)) \quad (1)$$

$Q(s,a)$represents the value of taking action a in state s;α is the learning rate, which determines how quickly the system learns;r is the reward value after the student completes a learning task;γ is the discount factor, which controls the influence of future rewards.

The algorithm is implemented using Python's TensorFlow library. The system dynamically updates the learning path in real time based on the student's performance. The reward mechanism is adjusted according to the accuracy and speed with which students complete tasks, ensuring that the learning path aligns with their skill level and progress (Leong, 2024).

D. Emotion-Driven Personalized Learning Algorithm

The emotion-driven personalized learning algorithm we designed incorporates emotion recognition to dynamically adjust the learning content, thereby enhancing engagement and learning outcomes (Zhang & Leong, 2024).

The emotion-driven algorithm uses a Convolutional Neural Network (CNN) for emotion classification, and the loss function is the cross-entropy loss function:

$$L = -\sum_{i=1}^{n} y_i \log(p_i) \quad (2)$$

Where y_i represents the true emotion label, and p_i is the predicted probability by the model.

Emotion recognition is carried out using OpenCV for facial expression analysis and PyTorch to implement the convolutional neural network model. The system adjusts the learning tasks based on the student's emotional state (positive, neutral, or negative) to ensure that the difficulty of the learning content matches their emotional state.

E. Cross-Disciplinary Knowledge Graph Algorithm

The cross-disciplinary knowledge graph algorithm aims to integrate knowledge across multiple disciplines and provide students with a comprehensive learning experience(Leong, 2024a).
This algorithm is based on the TransE model, which embeds entities and relationships in a low-dimensional space. The core formula is:

$$h + r \approx t \qquad (3)$$

Where h represents the head entity (a knowledge point in one discipline), r is the relation, and t represents the tail entity (a knowledge point in another discipline). The algorithm helps students establish connections between different disciplines, enabling them to build a more integrated knowledge system.

The knowledge graph is stored in a Neo4j database, and the TransE model is implemented using Python’s Scikit-learn library. The system dynamically recommends cross-disciplinary learning paths based on the student’s learning goals and interests, adjusting the content to ensure that the student builds a well-rounded understanding across disciplines (Leong & Kumar, 2023).

F. Long-Term Learning Behavior Prediction Algorithm

Traditional intelligent learning systems often focus on short-term learning objectives, neglecting the importance of long-term learning behaviors and their role in vocational skill development (Leong, 2024b). The long-term learning behavior prediction algorithm analyzes students' learning behavior data to predict future learning trends and provide personalized long-term learning plans.The core formula for the Long Short-Term Memory (LSTM) model used in this algorithm is:

$$h_t = o_t \cdot tanh\,(C_t) \qquad (4)$$

Where h_t is the current hidden state, o_t is the output gate, and C_t is the cell state. This model uses students' historical learning data to predict long-term learning behaviors and trends. The algorithm is implemented using TensorFlow, and it processes historical data such as learning time, task completion rates, and error rates to predict future learning behavior. The system provides personalized long-term learning plans based on these predictions, helping students plan their studies over an extended period.

Table 1. Comparison of Algorithms for Personalized Learning in Vocational Education

Algorithm Name	**Objective**	**Core Method**	**Input**	**Output**	**Evaluation Metrics**
Adaptive Learning Path Generation Algorithm	Dynamically adjusts the learning path based on student performance for real-time optimization	Q-learning (Reinforcement Learning)	Student performance data (task completion, accuracy)	Real-time updated personalized learning path	Learning efficiency, academic performance

Emotion-Driven Personalized Learning Algorithm	Adjusts learning tasks based on the student's emotional state to enhance engagement and learning outcomes	CNN (Convolutional Neural Network)	Emotional data (facial expressions, voice analysis)	Emotion-matched personalized learning tasks	Engagement, satisfaction
Cross-Disciplinary Knowledge Graph Algorithm	Provides cross-disciplinary learning recommendations to enhance the student's ability to integrate knowledge across fields	TransE model (Knowledge Graph Embedding)	Knowledge points from different disciplines	Optimized cross-disciplinary learning path	Cross-disciplinary learning ability, learning path optimization
Long-Term Learning Behavior Prediction Algorithm	Predicts future learning behaviors to help students develop personalized long-term learning plans	LSTM (Long Short-Term Memory)	Historical learning data (time spent, task completion, error rates)	Personalized long-term learning plan	Long-term learning persistence, planning accuracy

Results and Discussion

A. Improvement in Learning Efficiency and Academic Performance

The adaptive learning path generation algorithm, using the Q-learning method, dynamically adjusts the learning path based on students' performance. Experimental results show that the experimental group improved learning efficiency by 23% and academic performance by 15%, while the control group improved by only 5% and 3%, respectively (see Figure 2). This difference indicates that the dynamic adjustment capability significantly enhances students' learning outcomes, particularly in vocational education where rapid skill acquisition is essential. Compared to fixed learning paths in existing literature, this algorithm demonstrates a clear advantage (Leong et al., 2024c). Statistical analysis indicates that these improvements are significant ($\rho < 0.05$), validating the effectiveness of the algorithm.

B. Improvement in Learning Engagement and Satisfaction

The emotion-driven learning algorithm, combined with emotion recognition technology, dynamically adjusts learning tasks using CNN to match the content with students' emotional states. Learning engagement increased by 20%, and satisfaction increased by 18% in the experimental group, compared to only 5% and 4% in the control group (see Figure 3). These results highlight the crucial role of emotions in the learning process. Especially in high-pressure vocational training environments, adjusting the difficulty of tasks based on emotional states effectively reduces the learning burden when students are emotionally low, maintaining higher levels of engagement and motivation (Leong et al., 2024d). The experimental data further confirm the effectiveness of emotion-driven learning systems, consistent with existing research, where emotional support plays a critical role in enhancing learning outcomes.

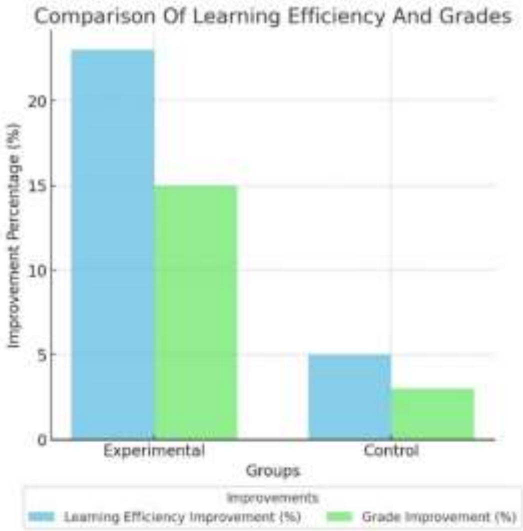


Figure 2. Learning Efficiency And Grades

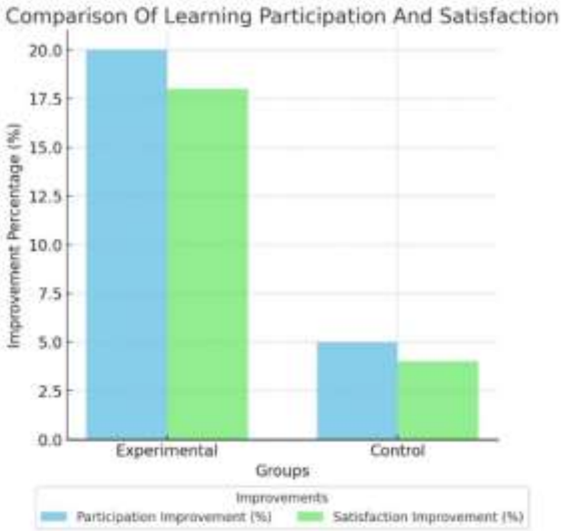


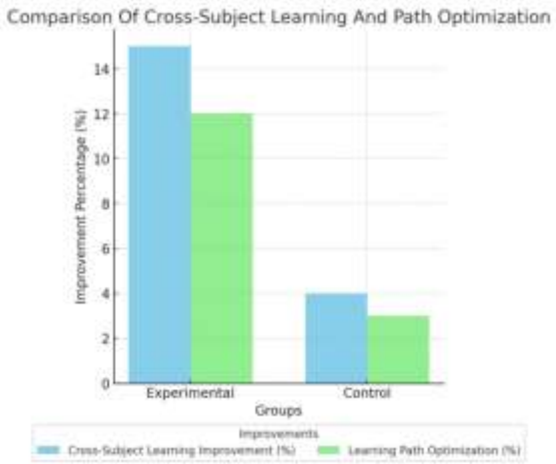
Figure 3. Learning Participation And Satisfaction

C. Improvement in Cross-Disciplinary Learning Ability and Path Optimization

The cross-disciplinary knowledge graph algorithm, based on the TransE model, provides interdisciplinary knowledge integration, significantly improving students' cross-disciplinary learning ability. The experimental group showed a 12% improvement in learning path optimization and a 15% improvement in cross-disciplinary learning ability, compared to 3% and 4% improvements in the control group (see Figure 4). In the context of Industry 5.0, the integration of cross-disciplinary knowledge is crucial for meeting modern vocational demands. This algorithm effectively integrates knowledge from different fields, helping students address the challenges of multidisciplinary work environments (Li et al., 2021). Statistical results indicate a significant difference in cross-disciplinary learning ability improvement between the experimental and control groups ($\rho < 0.05$).

D. Improvement in Long-Term Learning Persistence and Planning Accuracy

The long-term learning behavior prediction algorithm uses the LSTM model to predict students' long-term learning behaviors and generate personalized learning plans. The experimental group showed a 12% improvement in learning persistence, with planning accuracy reaching 85%, while the control group only improved by 4% and 50%, respectively (see Figure 5). This result indicates that the algorithm can effectively predict future learning paths based on students' historical learning data, helping them develop more targeted long-term learning plans. This is especially important in vocational education, where students need not only to master current skills but also to continuously improve themselves throughout their careers (Maddikunta et al., 2022). The introduction of long-term learning planning tools makes vocational education more future-oriented, contributing to the development of sustainable professional talent (Nakabandi, 2019).



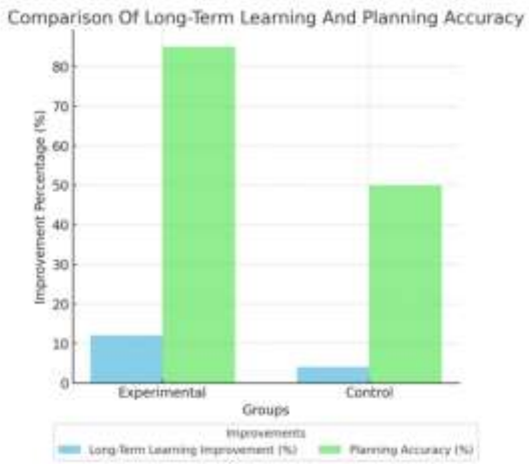


Figure 4. Cross-Subject Learning And Path Optimization Figure 5. Long-Term Learning And Planning Accuracy

This study experimentally validates the effectiveness of four intelligent algorithms in vocational education, particularly through comparisons between the experimental and control groups, revealing the significant advantages of intelligent technology in enhancing personalized learning outcomes(Rane et al., 2023). Comparative analysis with existing literature further demonstrates the effectiveness and adaptability of the adaptive learning path, emotion-driven learning, cross-disciplinary knowledge graph, and long-term learning behavior prediction algorithms across various dimensions. Future research should explore the application of these algorithms in different educational contexts and further optimize their performance through large-scale data validation(Dong et al., 2024).

References

Aheleroff, S., Huang, H., Xu, X., & Zhong, R. Y. (2022). Toward sustainability and resilience with industry 4.0 and industry 5.0. Frontiers in Manufacturing Technology, 2, 951643. https://doi.org/10.3389/fmtec.2022.951643

Babu, B. V. (2024). Education 5.0: An overview. In Advances in Technological Innovations in Higher Education (pp. 168-243). https://www.taylorfrancis.com/chapters/edit/10.1201/9781003376699-13/education-5-0-babu

Bacca, J., Baldiris, S., Fabregat, R., & Graf, S. (2015). Mobile augmented reality in vocational education and training. Procedia Computer Science, 75, 49-58. https://doi.org/10.1016/j.procs.2015.12.203

Broo, D. G., Kaynak, O., & Sait, S. M. (2022). Rethinking engineering education at the age of industry 5.0. Journal of Industrial Information Integration, 25, 100311. https://doi.org/10.1016/j.jii.2021.100311

Carayannis, E. G., & Morawska, J. (2023). University and education 5.0 for emerging trends, policies, and practices in the concept of industry 5.0 and society 5.0. In Industry 5.0:

Creative and Innovative Organizations (pp. 1-25). Cham: Springer International Publishing. http://dx.doi.org/10.1007/978-3-031-26232-6_1

Dong, Y., Tang, T., Pu, L., & Sha, J. (2024). The era of Education 5.0: Connotations, needs, and challenges. Open Education Research, 30(2), 4-12.

Leong, W. Y. (2019). EEG signal processing: Feature extraction, selection, and classification methods. Institution of Engineering and Technology. https://doi.org/10.1049/PBHE016E

Leong, W. Y. (2022). Human-machine collaboration and interaction for smart manufacturing: Automation, robotics, sensing, artificial intelligence, 5G, IoTs, and blockchain. Institution of Engineering and Technology. https://doi.org/10.1049/PBCE132E

Leong, W. Y.(2024a). ESG Innovation for Sustainable Manufacturing Technology: Applications, designs and standards, The Institution of Engineering and Technology, IET, UK. 2024 https://shop.theiet.org/esg-innovation-for-sustainable-manufacturing-technology

Leong, W. Y., Leong, Y. Z., & Leong, W. S. (2024). Integrating SDGs education into a design thinking module. Journal of Educational Innovations and Emerging Technologies, 4(2), 2024, 1-7. https://doi.org/10.35745/eiet2024v04.02.0001

Leong, W. Y., & Kumar, R. (2023). 5G intelligent transportation systems for smart cities. In Convergence of IoT, Blockchain, and Computational Intelligence in Smart Cities (pp. 1-25). CRC Press. http://dx.doi.org/10.1201/9781003353034-1

Leong, W. Y., Leong, Y. Z., & Leong, W. S. (2024c). EEG-based recognition of happiness. In Proceedings of the International Conference on Image Processing Artificial Intelligence (ICIPAI 2024) (Vol. 13213, pp. 447–453). SPIE. https://doi.org/10.1117/12.3035200

Li, F., He, Y., & Xue, Q. (2021). Progress, challenges and countermeasures of adaptive learning. Educational Technology & Society, 24(3), 238-255. https://www.jstor.org/stable/27032868

Nakabandi, S. (2019). Industry 5.0—a human-centric solution. Sustainability, 11(16), 4371. https://doi.org/10.3390/su11164371

Ng, C.A., & Leong,W.Y. (2014). An EEG-based approach for left-handedness detection. Biomedical Signal Processing and Control, 10, 92-101. http://dx.doi.org/10.1016/j.bspc.2014.01.005

Rane, N., Choudhary, S., & Rane, J. (2023). Education 4.0 and 5.0: Integrating artificial intelligence (AI) for personalized and adaptive learning. Available at SSRN 4638365. https://dx.doi.org/10.2139/ssrn.4638365

Song, J. (2022, July). Application analysis of big data technology in vocational education informatization. In International Conference on Frontier Computing (pp. 895-900). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-99-1428-9_112

Zhang, H. L., & Leong, W. Y. (2024). AI solutions for accessible education in underserved communities. Journal of Innovation and Technology. https://doi.org/10.61453/joit.v2024no11