Integrating Artificial Intelligence into Vocational Education: A Technical Application Framework Based on the 3E Model

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Abstract

Driven by machine learning, computer vision and immersive technologies, the application of AI in vocational education has moved from theoretical exploration to systematic implementation. This paper proposes a 3E model - a technology framework encompassing education (AI curriculum design), experience (virtual reality training ecosystem) and employment (industry-academia-research collaboration) - to address the skills gap in smart manufacturing and digital industries. Through an empirical case study involving 10 vocational schools and 15 industry partners, we demonstrate how AI tools can improve pedagogical efficiency, skills acquisition and employability. The framework also addresses technical challenges, such as rapid obsolescence and human resistance, and provides actionable insights for educators and policymakers to optimise AI-powered vocational systems.

CCS Concepts

• **Applied computing** → Education; Computer-assisted instruction.

Keywords

Artificial Intelligence, Vocational Education, Technical Application

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1 Introduction

Vocational education plays a key role in linking academic knowledge to industrial needs and providing learners with employable skills adapted to technological advances. However, traditional vocational models have tended to prioritise rote learning over adaptive problem solving - a limitation that is exacerbated by the rise of artificial intelligence and automation. To address this gap, this study proposes the 3E model, which integrates AI into vocational programmes through three interrelated pillars: education (AI-driven learning), experience (immersive training) and employment (industry-aligned outcomes). By focusing on real-world applications such as industrial robot programming, AI-driven quality inspection and virtual factory simulation, the model aims to align classroom learning with real-world industrial practices.

The experiment is based on empirical case studies from 10 vocational schools and 15 industry partners, and surveys and analyses students in five smart manufacturing courses offered by these schools and partners: artificial intelligence, industrial robotics, mobile application development, and automotive maintenance.The theoretical foundation of the 3E model is derived from constructivist learning theory, which emphasises active participation and context-based knowledge acquisition. Artificial intelligence has become a key support tool for modern vocational education by providing personalised learning experiences, simulating complex industry scenarios, and dynamically adapting to the needs of the labour market. In this paper, the feasibility of the model is verified through a longitudinal case study in terms of student performance, skill level and post-graduation outcomes.

2 Technical Application Framework: The 3E Model

2.1 Education: AI-Driven Core Courses

At the heart of the education pillar is the integration of AI technologies into vocational curricula to promote personalised and competency-based learning. Teachers of veterinary medicine in German vocational schools have attempted to integrate AI into their teaching, focusing mainly on specific and practical teaching levels in vocational schools[1].

A notable impact of AI is that it enables personalised educational experience[2]. For example, Table 1 shows machine learning (ML) algorithms are embedded in courses such as *Fundamentals of AI Algorithms*, where students use Python and TensorFlow to train models for predictive maintenance and anomaly detection. Over 64 credit hours, students work on programming tasks to analyse sensor data from industrial equipment, developing theoretical understanding and practical problem-solving skills.

Computer Vision (CV) is another major focus, integrated into courses such as Computer Vision Application Development. Students have used OpenCV to build a real-time defect detection system for a production line, and achieved 93% accuracy in a project using CNNs to detect cracks in automotive parts. These applications not only deepen domain expertise, but also foster adaptability to industry-specific challenges.

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Table 1: Core Courses and Credit Hours Allocation of the 3E Training Model (Class Size: 30 Students).

Training Module	Course/Activity Name	Credit Hours	Core Content	Participation Rate
Education	AI Aigorithm Fundamentals	64	Machine learning, deep learning principles, and programming practice	95%
	Industrial Robot Control Technology	72	Robot kinematics, PLC programming, and simulation	92%
	Computer Vision Application Development	48	OpenCV, image processing, and real-time detection system development	95%
Experience	Industrial Robot Training Workshop	120 (Practical)	Industrial robot operation, fault diagnosis, and maintenance	96%
	Enterprise Project Internship	80(Project Cycle)	Participation in AI quality inspection system development and smart warehouse optimization	90%
Employment	Industry-Academia Joint Training	40 (Enterprise Lectures)	Career planning guidance and job skill enhancement by industry mentors	98%

Natural language processing (NLP) further enhances the educational experience through intelligent teaching and learning systems. A team of researchers in Indonesia studied the integration of AI in vocational education, and the results showed that the implementation of AI can improve student learning outcomes and efficiency[3]. Transformer-based models (e.g. GPT-4) analyse student queries to generate adaptive feedback that enables granular competency mapping and real-time adjustment of learning trajectories. A comparative experiment with 30 students in the 3E modelling group and a traditional control group showed a 15% higher average score, which was attributed to the AI's ability to effectively address individual learning gaps.

2.2 Experience: Virtual-Real Training Ecosystems

The Experiential Pillar emphasises immersive learning through AI-powered simulations and industry collaboration. For example, virtual reality (VR) workshops allow students to safely practice high-risk tasks such as commissioning robotic arms, reducing equipment wear and tear costs by 30 percent. These simulations also provide the opportunity to troubleshoot assembly lines in a controlled environment that mirrors real industrial scenarios.One case study demonstrated significant improvements in student engagement, discipline and personalised learning outcomes by integrating AI monitoring, with a 25% increase in classroom interactions and a 40% reduction in disciplinary issues[4].

2.3 Employment: Industry-Academia Synergy

The Employment Pillar ensures that training outcomes meet current and future industry needs through dynamic curriculum updates and strategic partnerships. Artificial intelligence-driven labour market analysis tools continuously scan hiring trends to identify emerging skills, such as vision-based troubleshooting for automotive manufacturers. These insights inform curriculum adjustments to ensure learners gain relevant skills.

Partnerships with companies such as Huawei, BYD and logistics companies ensure that ≥85% of graduates are employed in AI-related positions, and their salaries are 18% higher than the industry average (Table 2). In particular, the AI maintenance centre established with BYD provides students with internships on new energy vehicle production lines, directly linking classroom learning to employment opportunities.

2.4 Results: Model validation based on experimental data

Table 3 shows the results of the comparison between the 3E model (experimental group, 30 students) and traditional teaching (control group, 30 students) on the five core dimensions. The experimental group scored significantly higher than the control group in terms of GPA (87.5 vs. 72.3), skills certification pass rate (92% vs. 65%), and employment in related AI fields (85% vs. 78%). The experimental group scored 31% higher on innovation skills (4.5/5) than the control group (3.2/5), highlighting the role of AI-driven project-based learning in fostering advanced problem-solving and practical skills. Taken together, these results validate the effectiveness of the 3E model in transforming vocational education through personalised learning, immersive training ecosystems, and industry-academia-research collaborations, shifting the focus from knowledge dissemination to systemic competency development.

The above experimental results verify the effectiveness of the 3E model and provide empirical evidence for the design of the subsequent realisation mechanism.

3 Implementation Mechanisms

3.1 Teacher Professional Development

Although teacher competence is a key determinant of successful AI adoption, there is still a need for a comprehensive framework to systematically improve teachers' AI technological competence and pedagogical approaches to meet educational goals and industry needs.

Based on the 3E (Education, Experience, Employment) model proposed in the study, teacher training programmes need to integrate technical competencies, pedagogical innovations and industry partnerships to meet the changing needs of vocational education[5].

Table 2: Enterprise Collaboration and Graduate Tracking Data (Past 3 Years).

Enterprise Type	Number	Job Opportunities	Average Salary (Monthly)	Industry Average (Monthly)	Promotion Speed (Years)
Smart Manufacturing	8	120	¥8,500	¥7,200	2.5 (Supervisor Level)
Internet Technology	5	80	¥9,200	¥8,000	2.2 (Technical Expert)
New Energy & Automotive	2	40	¥8,000	¥6,800	2.0 (Engineer)

Table 3: Comparative Experiment Between 3E Model and Traditional Teaching (Group: 30 Students).

Comparison Dimension	3E Model Experimental Group	Traditional Teaching Control Group	Difference Analysis
Average Score Improvement	87.5 (↑15%)	72.3 (↑5%)	AI-assisted teaching significantly enhances learning outcomes
Skill Mastery Rate	92% passed industrial robot certification	65% passed basic skill assessment	Practical workshops and enterprise projects improve hands-on capabilities
Employment Rate (1 Year)	94% (88% in relevant fields)	78% (62% in relevant fields)	Industry-academia collaboration significantly improves employment quality
Innovation Capability Score	4.5/5 (project-based evaluation)	3.2/5 (exam-based evaluation)	Real-world projects drive innovative thinking

Teacher training needs to be implemented and resourced in phases. The initial phase should prioritise needs assessment through surveys and interviews to identify gaps in AI literacy and teaching practices. For example, research has shown that teacher resistance to AI adoption is often due to unfamiliarity with new teaching tools and requires contextualised interventions such as demonstration projects and collaborative lesson planning. For example, a three-phase implementation plan could be used to ensure progressive skills development, starting with online courses and workshops, followed by project-based collaboration with industry mentors, and ending with a public demonstration of AI-enhanced teaching outcomes.

The foundation of this training lies in a tiered approach that accommodates varying levels of teacher expertise. For novice educators, foundational training modules should focus on core AI concepts, such as machine learning principles, Python programming, and data preprocessing techniques. Practical sessions involving tools like TensorFlow and OpenCV enable hands-on experience in developing basic AI models, such as image classification systems or predictive maintenance algorithms. These foundational skills are critical for enabling teachers to understand AI's role in modern vocational training, as demonstrated in courses like AI Algorithm Fundamentals and Computer Vision Application Development, where students achieved 93% accuracy in defect detection projects.

Moving to intermediate and advanced levels, training should emphasise deeper technology integration and interdisciplinary applications. For example, educators with a basic knowledge of edge computing devices such as the Raspberry Pi could participate in a workshop that facilitates real-time data processing in a simulated industrial environment. This type of training aligns with the experiential pillar of the 3E model, where virtual-real ecosystems allow educators to design immersive learning scenarios, such as commissioning a robotic arm in a VR environment, while increasing student engagement. In addition, advanced training should introduce emerging technologies such as federated learning and generative AI, enabling educators to develop AI-driven curricula that bridge disciplines such as renewable energy optimisation or smart city design. This tiered progression mirrors the tiered course structure observed in the study, with the professional and advanced levels focusing on industry-specific applications and cross-disciplinary innovation.

At the same time, qualitative methods are needed to assess the effectiveness of faculty training, including reflective journals and peer reviews, as well as feedback from companies to capture faculty adaptability and effectiveness in integrating AI tools.

3.2 Curriculum Reconstruction

The course is organised into a hierarchical structure to balance depth and flexibility: 1. Foundation Level: Introduces programming fundamentals (Python) and basic data acquisition techniques.

2. Specialised Tier: Focuses on industry-related applications such as ML for predictive maintenance of HVAC systems and CV-based quality control systems.

3. Advanced Tier: Promotes interdisciplinary innovation through AI-driven renewable energy optimisation and smart city design projects.

This structure ensures that learners build essential skills while pursuing specialised knowledge and exploring cross-disciplinary opportunities.A study at Pelita Harapan School showed that students were highly aware of the potential benefits of generative AI and supported its integration into the curriculum[6].

3.3 Technological Infrastructure

In terms of technical deployment, the cost-effective cloud-edge hybrid architecture supports AI-driven learning by integrating cloud labs, edge devices and optimised networks. The cloud lab, powered by AWS and AliCloud GPU clusters, handles compute-intensive tasks such as model training, significantly reducing the initial hardware investment. Meanwhile, edge devices such as Raspberry Pi and NVIDIA Jetson units enable real-time processing of sensor data during VR training and physical robotics operations. To ensure seamless interaction between these components, a 5G network was deployed to provide low-latency communication between cloud servers and edge devices, which is critical for creating immersive VR environments. This infrastructure model not only minimises costs, but also aligns with industry-standard computing paradigms and prepares students for the demands of the modern workplace.

For the average school, the recommended budget management approach is to integrate cost-effective cloud services, affordable edge devices and optimised local networks. For example, at the cloud layer, schools can leverage domestically available GPU computing resources (such as Tencent Cloud Education Edition and Huawei Cloud AI Labs) through a pay-as-you-go model, complemented by free storage solutions (such as Tencent Micro Cloud Education and Ding Language Archive). Over time, schools can integrate more advanced edge devices (e.g., DJI Education Suite) and locally deployed GPU servers (via the Huawei Kunpeng ecosystem), and partner with universities or technology companies for equipment donations and technical guidance. This approach balances cost control and practicality in an educational environment.

4 Challenges and Mitigation Strategies

4.1 Technology dependency

It is important to emphasise that the integration of AI in vocational education and training can easily raise ethical issues related to AI. Some scholars have argued that AI may lead to student dependency on technology and hinder the development of innovation[7]. Generative AI may undermine the fairness of the educational environment in everyday teaching, such as examinations and assessments. Therefore, it is necessary for schools to establish systems to prevent cheating using AI and relying on AI to cheat. To mitigate this, the 3E model uses balanced skill development frameworks, such as hybrid assessment systems that combine AI-driven assessments (e.g. automated coding assessments) with manual skill demonstrations (e.g. mechanical assembly tasks). For example, in courses such as Applications of Artificial Intelligence Technology, students can verify AI decisions by comparing test algorithms with human inspection results.

Ensuring the fairness of AI-based assessments is another ethical challenge, particularly as generative AI has the potential to undermine academic integrity. To prevent misuse, the framework integrates monitoring tools that are enhanced with interpretable reports. These systems detail how to flag behavioural anomalies (e.g. eye movement bias) and address allegations of algorithmic bias. In addition, institutional governance plays a key role in AI ethics management. For example, a cross-functional AI ethics committee composed of educators, IT experts and legal counsel should review AI tools at least twice a year.

These ethical strategies are woven throughout the pillars of the 3E model. In the educational component, the ethics module accounts for 10% of the core AI course credits. The experiential pillar includes virtual reality simulations with ethical dilemmas, and for employment, industry partners commit to an ethical AI charter that ensures graduate employment adheres to privacy and fairness standards. By institutionalising ethical safeguards, from technological solutions to policy mechanisms, the enhanced 3E model ensures that AI integration reinforces the human-centred goals of vocational education.

4.2 Human-Centered Adaptation

In order to address teachers' resistance to the adoption of AI, mainly due to unfamiliarity with new teaching methods, this study implemented a contextualised intervention. This included a demonstration project to show the positive impact of AI on student achievement through comparative experiments, such as the significant average score increase of 15% observed in Table 2. In addition, collaborative design workshops were conducted to engage teachers in the co-creation of AI-enhanced lesson plans, thereby fostering a sense of ownership and confidence. In addition, an ongoing support network was established through a mentoring programme that paired novice teachers with AI-certified peers to ensure ongoing mentoring and professional development. For example, an education team developed a personalised education model based on AI technology. The model uses AI to personalise the assessment of content, pedagogy and actual outcomes, with the aim of increasing student interest and engagement [8].

5 Conclusion

The 3E model demonstrates the transformative potential of AI in vocational education, validated by empirical evidence of improved teaching effectiveness, skills acquisition and employment outcomes. In addition to smart manufacturing, the 3E Model can be extended to multiple industries by customising AI courses to meet specific industry needs. To ensure adaptability, the core AI curriculum (such as Python programming and data pre-processing) remains consistent, while specialised layers include industry-specific datasets and tools. For example, an agriculture app might include an AI precision farming module that uses satellite imagery and climate data to optimise crop yield predictions and pest detection. In retail, an AI-powered customer behaviour analytics course could use natural language processing tools to analyse consumer feedback and develop personalised marketing strategies. Meanwhile, healthcare courses could use anonymised patient data to integrate technology and ethics. By combining technology implementation with industry realities, vocational education can be the cornerstone of an AI-driven economy, fostering sustainable innovation and workforce competitiveness.

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