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Original Paper

A Project-Based Teaching Model for the Course *Fundamentals and Applications of Artificial Intelligence* in Higher Vocational Education under the Perspective of Industry–Education Integration

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Abstract

In the context of new engineering education and industrial digital transformation, the course Fundamentals and Applications of Artificial Intelligence in higher vocational colleges urgently needs to align more closely with industry demands. Guided by the concept of industry–education integration, this paper proposes a project-based teaching model grounded in real enterprise projects, forming a closed-loop system of "school–enterprise collaboration, task-driven learning, and intelligent evaluation." By embedding project tasks in application scenarios such as intelligent manufacturing, smart transportation, and low-altitude economy, the model cultivates students' abilities in AI application and problem solving. The research results show that this approach significantly enhances students' professional adaptability and innovative practice skills, providing an innovative paradigm for the collaborative cultivation of AI talents between higher vocational institutions and industry.

Keywords

Industry–education integration, project-based teaching, Fundamentals and Applications of Artificial Intelligence, school–enterprise collaboration, professional competence

1. Introduction

1.1 Background of AI Education Reform in Higher Vocational Institutions

In recent years, the rapid development of artificial intelligence (AI) technologies such as machine learning, big data analytics, and intelligent automation has profoundly reshaped industrial structures and occupational requirements worldwide. Governments and educational authorities, including China's Ministry of Education, have emphasized the importance of cultivating AI-related competencies among technical and vocational students to meet the demand for "new engineering" and "digital economy" talents. Higher vocational institutions, as the primary providers of application-oriented education, are therefore undertaking an urgent transformation toward AI-driven curriculum reform.

The course Fundamentals and Applications of Artificial Intelligence serves as an essential entry point for students to understand AI principles and acquire basic skills in algorithmic thinking, data processing, and model application. However, in many vocational colleges, the course is still delivered in a conventional, theory-heavy format, often detached from real industrial contexts. Students tend to focus on programming syntax or algorithmic details without understanding how AI is applied in practical domains such as smart manufacturing, intelligent logistics, or digital construction. This disconnection between learning and practice leads to low engagement, limited creativity, and insufficient problem-solving abilities among students. Consequently, it is necessary to establish a teaching model that bridges theoretical instruction with authentic industrial applications through systematic reform and integration.

1.2 The Urgency of Industry–Education Integration in AI Curriculum

The integration of industry and education has become a strategic pathway to enhance the relevance and effectiveness of vocational training in the era of intelligent transformation. The deep convergence of AI technology and industry—ranging from intelligent transportation and healthcare to financial technology and the low-altitude economy—has generated new job categories that require hybrid competencies combining technical literacy, project management, and innovation awareness. However, traditional vocational education often lags behind industrial development due to rigid curricula, insufficient enterprise participation, and outdated evaluation methods.

Industry–education integration provides a feasible mechanism to overcome these challenges by aligning learning objectives with real-world skill requirements. Through cooperative project development, enterprise mentorship, and task-based learning, students can engage in authentic AI application scenarios, transforming theoretical understanding into actionable competence. For instance, collaborating with enterprises on projects involving visual inspection systems, data-driven decision platforms, or smart IoT devices can allow students to experience the entire AI development cycle—from data collection and preprocessing to model deployment and performance evaluation.

Moreover, the introduction of industry resources not only enhances the authenticity of learning tasks but also facilitates the co-construction of curriculum standards, evaluation rubrics, and competency models that reflect the current state of industrial practice. Therefore, developing an AI curriculum rooted in industry–education integration is not merely an educational innovation but a necessary response to the transformation of labor markets and industrial upgrading. It ensures that vocational education remains dynamic, future-oriented, and aligned with the evolving ecosystem of intelligent industries.

1.3 Research Objectives and Innovation Points

This research aims to explore and construct a **project-based teaching model** for the course Fundamentals and Applications of Artificial Intelligence under the perspective of **industry–education integration**. The primary objectives are threefold:

(1) **To design** a collaborative framework that connects higher vocational institutions with industrial partners in developing AI-related teaching projects based on real enterprise needs.

(2) **To implement** project-based learning (PBL) strategies within the AI curriculum, integrating task-driven learning, intelligent tools, and multi-dimensional evaluation systems.

(3) **To evaluate** the effectiveness of the model in enhancing students' applied skills, problem-solving capabilities, and innovation awareness through empirical analysis and data comparison.

The innovation of this study lies in the construction of a **"School–Enterprise–Project" closed-loop model**, which emphasizes mutual participation in curriculum design, project implementation, and learning evaluation. Unlike traditional PBL approaches that focus solely on academic tasks, this model incorporates industrial datasets, AI software platforms, and enterprise mentorship to ensure high fidelity between classroom learning and workplace demands. Furthermore, it introduces **intelligent evaluation mechanisms** supported by learning analytics and AI-based feedback systems to continuously optimize teaching processes and learning outcomes.

Through this model, the research contributes not only to the modernization of AI education in vocational institutions but also to the theoretical enrichment of industry–education integration practices in the context of digital transformation.

2. Literature Review

2.1 Overview of Fundamentals and Applications of Artificial Intelligence Course in China's Vocational Education

In the context of China's educational modernization strategy, artificial intelligence (AI) has been identified as a key driver of the country's transformation toward a digital and intelligent economy. Since the release of policy frameworks such as the New Generation Artificial Intelligence Development Plan (2017) and the Modern Vocational Education Reform Plan (2019), AI-related courses have been systematically introduced into higher vocational institutions. Among these, the course Fundamentals and Applications of Artificial Intelligence has become the foundational subject for cultivating students' digital literacy and technical problem-solving abilities.

This course typically covers topics including AI principles, machine learning algorithms, neural networks, data preprocessing, natural language processing, and computer vision. In addition to technical content, it emphasizes the development of computational thinking, logical reasoning, and innovation awareness. However, the current implementation of the course in many vocational colleges tends to focus on theoretical delivery or software tutorials, often lacking integration with real industrial applications. The gap between course objectives and workplace requirements leads to limited skill transferability.

Recent reforms in vocational education advocate a transformation from “knowledge-based teaching” to “competency-oriented learning.” The AI+Education Action Plan (2024) further encourages the establishment of AI application scenarios in teaching and the use of intelligent tools to support personalized learning. Therefore, the Fundamentals and Applications of Artificial Intelligence course is not only a technical foundation course but also a critical platform for promoting interdisciplinary innovation and preparing students for future intelligent industries.

2.2 Current Studies on Project-Based Learning (PBL) and Competency-Based Education

Project-Based Learning (PBL) has been widely recognized as an effective pedagogical strategy for fostering deep learning, practical competence, and innovation. Rooted in Dewey’s pragmatism and Kolb’s experiential learning theory, PBL emphasizes learning through authentic projects that integrate knowledge construction, teamwork, and reflection. In vocational education, PBL aligns closely with competency-based education (CBE), which prioritizes demonstrable skills and performance outcomes rather than rote knowledge acquisition.

Research shows that integrating PBL into technical disciplines enhances students’ motivation and engagement, particularly when projects are contextualized within real-world problems (Bell, 2010; Blumenfeld et al., 2021). In the field of AI education, several studies highlight the value of project-based approaches for improving algorithm comprehension, data analysis skills, and ethical awareness (Chen & Zhang, 2023). Furthermore, PBL facilitates the integration of multidisciplinary knowledge—combining data science, programming, and domain expertise—which is essential for complex AI applications.

In China’s vocational education reform, PBL has been adopted as a key method under the Work-Integrated Learning and 1+X Certification frameworks. However, its implementation in AI-related courses remains in an exploratory stage. The lack of standardized project evaluation systems, teacher guidance in AI applications, and collaboration with enterprises limits the full realization of its benefits. Hence, there is a growing need to develop an AI-specific PBL model that combines academic knowledge, industrial data, and intelligent assessment to form a holistic competency development pathway.

2.3 Challenges in Aligning AI Curricula with Industrial Needs

Although the importance of AI education is widely recognized, significant challenges persist in aligning curricular content with the rapidly evolving industrial ecosystem. First, the **technology–curriculum lag** problem is evident: industrial AI applications evolve far more quickly than academic curricula can adapt. This results in outdated content that no longer reflects current practices in intelligent manufacturing, smart logistics, or data-driven decision-making.

Second, there exists a **disconnect between theoretical instruction and practical application**. Many AI courses emphasize algorithmic formulas or software operation skills without contextualizing them in enterprise projects. Consequently, students may possess technical knowledge but lack the capacity to deploy AI solutions in real-world environments.

Third, **industry participation in curriculum development** remains limited. Enterprise professionals are seldom involved in course design, assessment, or mentoring. This absence of collaboration weakens the relevance of educational outcomes to employment needs. Additionally, **evaluation mechanisms** in many institutions focus on exams and coding assignments rather than comprehensive performance indicators such as project quality, teamwork, and innovation.

Finally, the shortage of **dual-qualified teachers**—instructors proficient in both pedagogy and AI technology—further constrains effective curriculum delivery. Without continuous professional development and enterprise exposure, teachers struggle to incorporate cutting-edge AI technologies or guide students through complex real-world projects. Overcoming these challenges requires a structural reform of AI curriculum design, teaching methods, and assessment models through deeper industry–education collaboration.

2.4 Theoretical Foundation: Constructivism and Experiential Learning Theory

The theoretical foundation of this research is grounded in **constructivism** and **experiential learning theory**, both of which emphasize active, learner-centered engagement and knowledge construction through practice. Constructivism, proposed by Piaget and Vygotsky, asserts that learners construct meaning through interaction with their environment rather than passively receiving information. In the context of AI education, this implies that students learn most effectively when they participate in authentic problem-solving and project development that mirrors industrial contexts.

Kolb's experiential learning theory further complements this view by proposing a cyclical process of learning consisting of four stages: concrete experience, reflective observation, abstract conceptualization, and active experimentation. When applied to AI education, these stages correspond to (1) engaging in enterprise-related projects, (2) reflecting on project outcomes, (3) abstracting theoretical principles from practice, and (4) reapplying those insights in new situations.

Combining these theories provides a strong rationale for the project-based model advocated in this study. The model situates students in **realistic learning environments** where knowledge is applied and recontextualized through experience. It also aligns with competency-based outcomes by promoting not only technical proficiency but also critical thinking, collaboration, and innovation—skills essential for success in the AI-driven economy.

In summary, constructivism and experiential learning offer a robust pedagogical foundation for integrating industry practice into the AI curriculum, supporting the formation of a continuous learning cycle that bridges theoretical understanding and applied competence.

3. Research Framework and Methodology

3.1 Research Design and Methodology Overview

This study adopts a **mixed-methods approach** combining both qualitative and quantitative analyses to explore the effectiveness of a project-based teaching model for the course Fundamentals and Applications of Artificial Intelligence under the framework of industry–education integration. The research is divided into three main stages: (1) model construction based on theoretical analysis and policy review, (2) pilot implementation of the model in selected higher vocational classes, and (3) empirical evaluation through data collection, performance analysis, and participant feedback.

Qualitative methods such as document analysis, expert interviews, and classroom observation were employed to identify core elements of industry–education collaboration and to construct the conceptual framework of the "School–Enterprise–Project" model. Quantitative methods, including surveys and performance evaluation metrics, were then used to validate the model's effectiveness in enhancing students' professional competencies and innovation skills.

The methodological rationale for this design lies in its ability to capture both **the structural characteristics** of the new teaching model and **its practical impact** on learners. A combination of these methods ensures the research outcome is both theoretically grounded and empirically robust. The study spans one academic semester (16 weeks) in which the project-based AI curriculum was implemented and evaluated.

3.2 Conceptual Framework of the "School–Enterprise–Project" Collaborative Model

The proposed model is based on the principle of **industry–education integration** and aims to form a dynamic, closed-loop collaboration system among schools, enterprises, and students. It emphasizes authentic learning tasks, AI tool integration, and intelligent evaluation feedback, thereby establishing a comprehensive ecosystem for continuous learning improvement.

In this model, the **school** acts as the organizer and academic guide, responsible for curriculum planning, resource integration, and teaching supervision. The **enterprise** serves as the co-developer of project content and the provider of real-world datasets, technical tools, and mentoring. The **students**, positioned as active learners and innovators, participate in project execution, data analysis, and solution development using AI platforms and industrial case materials.

The model operates through five interconnected stages forming a continuous feedback loop:

(1) **School–Enterprise Collaboration** – Joint curriculum design and project topic selection based on industrial needs.

(2) **Project Design and Task Planning** – Definition of learning goals, deliverables, and resource allocation.

(3) **Task Implementation and AI Tool Integration** – Application of AI platforms and datasets through teamwork.

(4) **Performance Evaluation and Reflection** – Intelligent evaluation using learning analytics, peer review, and enterprise feedback.

(5) **Continuous Improvement and Curriculum Optimization** – Updating teaching resources and project cases for the next iteration.

The collaboration process is iterative, ensuring that learning outcomes and enterprise feedback continuously inform curriculum reform and industrial engagement.

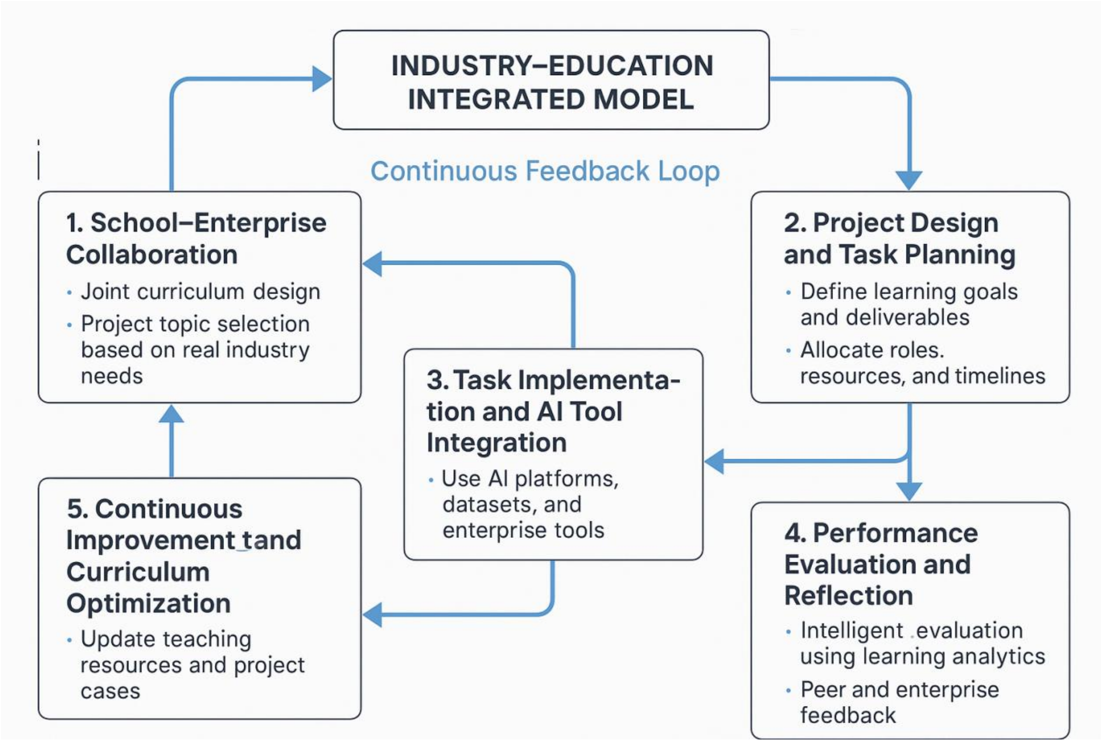

Figure 1. Framework of the Industry–Education Integrated Project-Based Model

Explanation: Figure 1 here illustrates the cyclical structure and interconnections among the five components described above, emphasizing feedback and iteration. This framework illustrates the **closed-loop structure** of the proposed teaching model:

(1) **School–Enterprise Collaboration** initiates joint curriculum and project co-development.

(2) **Project Design** converts industrial problems into learning tasks.

(3) **Implementation** integrates AI tools and collaborative practice.

(4) **Intelligent Evaluation** gathers performance data and feedback.

(5) **Continuous Improvement** feeds insights back into curriculum reform—forming an iterative, adaptive system.

3.3 Data Collection: Course Implementation and Participant Selection

The empirical study was conducted at a higher vocational college in Southwest China, where the Fundamentals and Applications of Artificial Intelligence course was redesigned according to the proposed project-based model. Two classes within the same academic program were selected for comparison:

(1) **Experimental Group (n = 46)**: Implemented the new industry–education integrated project-based model.

(2) **Control Group (n = 45)**: Followed the traditional lecture-based and exercise-driven teaching approach.

The same instructor team and syllabus were used to maintain comparability, while the experimental class incorporated enterprise case studies, industrial datasets, and AI tools such as TensorFlow, Python, and image recognition modules from enterprise partners.

Data sources included:

(1) **Pre- and post-course surveys** evaluating students' motivation, engagement, and self-perceived competence.

(2) **Project performance assessments**, including coding accuracy, model design, and innovation documentation.

(3) **Learning analytics data** collected from AI-assisted teaching platforms (e.g., participation frequency, task completion rate, and peer interaction records).

(4) **Qualitative interviews** with 10 students, 2 enterprise mentors, and 3 instructors to gain insights into learning experiences and implementation challenges.

To ensure reliability and validity, all instruments were pre-tested and reviewed by experts in AI education and vocational pedagogy. Quantitative data were analyzed using SPSS, while qualitative data underwent thematic coding to identify patterns related to skill development, teamwork, and innovation.

3.4 Evaluation Metrics: Learning Outcomes, Professional Competence, Innovation Ability

The evaluation system for this study was designed around three dimensions of student development, consistent with the objectives of the Fundamentals and Applications of Artificial Intelligence course and the principles of competency-based education:

(1) **Learning Outcomes (Knowledge and Skills Acquisition)**

This dimension measures the degree to which students master AI fundamentals, including data processing, algorithm implementation, and tool usage. Indicators include project completion rate, assessment scores, and AI tool proficiency. The post-course test and project rubric serve as the primary quantitative measures.

(2) **Professional Competence (Application and Problem-Solving Ability)**

This refers to students' capacity to apply AI knowledge in real or simulated industrial contexts. It is evaluated through project-based assessments, teamwork performance, and enterprise mentor reviews. Professional competence emphasizes transferability—how well students can translate classroom learning into work-oriented problem-solving skills.

(3) **Innovation Ability (Creativity and Reflective Thinking)**

Innovation ability is assessed through students' capacity to design original AI solutions, optimize algorithms, or propose novel applications. Evaluation methods include innovation reports, reflection journals, and peer assessments. The presence of creative problem-solving approaches in final projects is also used as an indicator of innovation growth.

Each dimension is weighted according to its relevance in vocational training objectives:

Learning Outcomes: **40%**

Professional Competence: **35%**

Innovation Ability: **25%**

A composite score is generated to evaluate overall learning effectiveness. Statistical comparisons between the control and experimental groups, along with correlation analysis between engagement metrics and competence development, provide empirical evidence for the model's effectiveness.

The comprehensive evaluation approach thus ensures a multidimensional understanding of the project-based model's educational impact—combining measurable cognitive outcomes with qualitative insights into student growth and adaptability.

4. Construction of the Project-Based Teaching Model

4.1 Key Principles of the Model: Authenticity, Task Orientation, and Reflection

The proposed project-based teaching model for the course Fundamentals and Applications of Artificial Intelligence is constructed upon three core pedagogical principles—**authenticity**, **task orientation**, and **reflection**—which serve as the guiding philosophy for curriculum design and implementation.

(1) Authenticity.

Authenticity ensures that learning activities mirror real-world professional contexts. In the AI domain, this means that the projects undertaken by students should stem from actual enterprise cases, real datasets, and technological challenges that reflect industrial realities. Authentic learning promotes relevance, motivation, and a sense of purpose, bridging the gap between academic theory and workplace practice. Through authentic projects, students engage not only in technical operations but also in decision-making, teamwork, and problem-solving under realistic constraints.

(2) Task Orientation.

Task orientation emphasizes the decomposition of complex projects into manageable, goal-driven learning tasks. Each task corresponds to a specific learning objective—such as model training, data preprocessing, or algorithm optimization—and contributes to the completion of the larger project. Task-based design allows for scaffolding, progressive skill acquisition, and adaptive learning pacing. It also encourages active participation, as students assume distinct roles (e.g., project leader, data analyst, or AI developer) within teams, simulating real enterprise workflows.

(3) Reflection.

Reflection transforms experience into learning. After each project milestone, students are required to analyze their outcomes, challenges, and decision processes through reflection reports and peer discussions. Teachers and enterprise mentors guide this process by offering targeted feedback. Reflection deepens conceptual understanding and fosters metacognitive awareness, which is essential for continuous improvement and professional growth in the rapidly evolving AI industry.

These three principles jointly create a learning ecosystem where students not only acquire technical skills but also develop critical thinking, collaboration, and lifelong learning habits—all vital to AI-driven careers.

4.2 Three-Phase Design

The implementation of the project-based model follows a **three-phase structure**—**Preparation**, **Implementation**, and **Evaluation**—which forms a cyclical and iterative process for sustained improvement.

(1) Preparation Phase – Selecting Enterprise-Aligned AI Projects

In the preparation phase, higher vocational institutions collaborate with enterprise partners to identify suitable project topics derived from real business challenges. Selection criteria include technical feasibility, data accessibility, and educational value. Typical sources include smart manufacturing firms, logistics companies, and technology service enterprises.

During this stage:

① Teachers and enterprise mentors co-design the project scope, expected deliverables, and evaluation rubrics.

② Students are introduced to relevant background knowledge, including AI concepts, software tools, and ethical considerations.

③ Learning groups (4–6 students) are formed based on skill diversity to ensure interdisciplinary collaboration.

④ A project plan is drafted, outlining milestones and task distribution.

This preparation process ensures alignment between **teaching objectives and industrial requirements**, establishing the foundation for authentic learning engagement.

(2) Implementation Phase – Guided Learning and AI Tool Application

The implementation phase constitutes the **core of the teaching model**. Under faculty guidance and enterprise mentorship, students carry out project tasks through iterative experimentation, data analysis, and model development. The use of AI tools such as Python, TensorFlow, PaddlePaddle, or Scikit-learn is emphasized, enabling students to gain practical experience with technologies applied in modern workplaces.

Key features of this phase include:

① **Task-driven learning:** Each subtask corresponds to an AI application process (e.g., image recognition, predictive analytics, or natural language processing).

② **Mentor feedback mechanism:** Enterprise engineers provide periodic feedback on students' model designs, ensuring industrial relevance.

③ **AI learning analytics:** Intelligent learning platforms track students' progress and generate individualized feedback based on participation frequency, accuracy, and creativity metrics.

④ **Interdisciplinary collaboration:** Students integrate knowledge from programming, data analysis, and domain expertise to build end-to-end AI solutions.

This guided practice cultivates both **technical proficiency** and **professional adaptability**, allowing students to internalize workplace standards and communication practices.

(3) Evaluation Phase – Multi-Dimensional Assessment and Iteration

The evaluation phase emphasizes **comprehensive and data-informed assessment**, ensuring that learning outcomes are measured across multiple dimensions. It combines formative and summative evaluations using the criteria outlined in Section 3.4—learning outcomes, professional competence, and innovation ability.

The assessment system consists of:

① **Instructor evaluation** of project deliverables (accuracy, efficiency, innovation).

② **Enterprise mentor review** based on workplace standards.

③ **Peer assessment** to evaluate teamwork, leadership, and collaboration.

④ **Intelligent analytics reports** generated from platform data on engagement and progress.

After the evaluation, a reflection workshop is conducted where students present their results, discuss limitations, and propose improvements. The collected feedback informs future curriculum revisions, completing the learning cycle. This iterative structure ensures that each project cohort contributes to the refinement of both the course design and institutional-industry collaboration mechanisms.

4.3 Integration of Industrial Partners and Real-World Datasets

The success of this model depends heavily on **effective industry integration**. To achieve this, the course establishes long-term partnerships with enterprises from AI-related sectors such as manufacturing automation, logistics optimization, and smart city infrastructure. These partners provide not only **project topics** but also **real-world datasets**, technical platforms, and expert mentorship.

Typical integration methods include:

① **Joint course development:** Enterprises co-design the curriculum and assessment standards to reflect actual occupational competencies.

② **Data and resource sharing:** Partners offer anonymized datasets from production lines, sensor systems, or customer behavior analytics to simulate real AI tasks.

③ **Dual mentorship system:** Each project team is jointly guided by a college instructor and an enterprise engineer, combining theoretical depth with practical insight.

④ **Workplace immersion:** Students may visit partner sites or engage in short-term internships to observe AI implementation in real operational settings.

Such integration ensures that the Fundamentals and Applications of Artificial Intelligence course remains current with industry advancements while embedding students in authentic professional ecosystems.

4.4 Example Project Cases

To validate the applicability of the proposed model, several representative projects were developed and implemented during the pilot study. These examples illustrate how industrial collaboration and AI technologies converge in real teaching contexts.

(1) Smart Parking Management System

Students collaborated with a local transportation company to design an AI-based parking system using image recognition to detect vacant spots and manage vehicle flow. The project integrated computer vision, edge computing, and data analytics. The enterprise provided sample datasets of parking lot images, while students trained CNN models to achieve over 90% accuracy in spot recognition.

(2) Intelligent Logistics Optimization Platform

Partnering with a logistics enterprise, students developed a machine learning model to optimize delivery routes and minimize fuel consumption. They used real GPS and traffic data to train predictive algorithms. The project emphasized teamwork between AI specialists and logistics management students, fostering interdisciplinary problem-solving.

(3) AI-Based Quality Inspection System for Manufacturing

In collaboration with a precision manufacturing firm, students built an AI system to identify surface defects in metal components using deep learning. The enterprise supplied industrial images and defect samples, enabling the class to simulate a production-line inspection process. This project enhanced students' understanding of data preprocessing, model validation, and industrial automation standards.

Each case demonstrates how **enterprise collaboration**, **project-driven learning**, and **AI tool application** collectively cultivate the competencies required by the modern digital economy. Furthermore, the iterative refinement of these projects across cohorts contributes to a repository of reusable teaching cases, sustaining continuous curriculum innovation.

5. Empirical Study and Data Analysis

5.1 Experimental Setting: Two Higher Vocational Classes (Control vs. Experimental Group)

To evaluate the effectiveness of the proposed industry–education integrated project-based teaching model, an empirical experiment was conducted in the Fundamentals and Applications of Artificial Intelligence course at a higher vocational college in Southwest China during the 2024–2025 academic year. Two parallel classes were selected for comparison based on equivalent academic backgrounds and entrance scores.

(1) **Control Group (n = 45):** Adopted the traditional lecture-based and exercise-driven instruction model, focusing primarily on algorithm teaching and programming assignments.

(2) **Experimental Group (n = 46):** Implemented the proposed project-based model, which integrated enterprise projects, real-world datasets, and AI tool platforms such as TensorFlow and Python for applied learning.

Both groups were taught by the same instructor team over a 16-week semester to ensure consistency. The course included 64 teaching hours, with identical theoretical content coverage but different teaching strategies and assessment criteria. The control group's evaluation relied on written tests and lab exercises, while the experimental group's evaluation included project performance, mentor feedback, peer assessment, and intelligent analytics.

The implementation environment for the experimental group was designed to simulate real industry scenarios—students worked in teams, collaborated with enterprise mentors online, and used enterprise-provided datasets (e.g., image recognition, logistics routing, or product inspection). This setting aimed to bridge academic learning with professional application, aligning teaching outcomes with the demands of the digital and intelligent economy.

5.2 Data Sources: Learning Analytics, Surveys, Project Performance Evaluation

Data for this study were collected through multiple sources to ensure comprehensive and reliable analysis:

(1) **Learning Analytics Data:** Extracted from the AI-assisted teaching platform, including student login frequency, task completion rate, coding accuracy, and participation in discussion forums. These data provided behavioral indicators of engagement.

(2) **Surveys:** Pre- and post-course questionnaires measured students' self-perceived growth in AI skills, problem-solving ability, innovation awareness, and teamwork. Cronbach's α reliability coefficients exceeded 0.85, confirming internal consistency.

(3) **Project Performance Evaluation:** Based on standardized rubrics co-developed with enterprise partners, assessing AI model accuracy, creativity of solutions, and technical documentation quality.

(4) **Mentor Feedback:** Industry mentors evaluated students' professional attitudes and collaboration competence using a 5-point Likert scale.

(5) **Interviews:** Supplementary qualitative interviews were conducted with selected students and instructors to interpret statistical results and identify implementation challenges.

The multi-source data collection approach enabled triangulation, enhancing the validity of the findings.

5.3 Quantitative Analysis of Student Outcomes

Quantitative analysis was performed using descriptive statistics and independent-sample t-tests to compare post-course outcomes between the control and experimental groups. The mean scores for five key indicators—AI application skills, problem-solving ability, innovation awareness, team collaboration, and learning motivation—were computed.

Table 1. Comparison of Learning Outcomes Between Control and Experimental Groups

Evaluation Indicator	**Control Group (n=45)**	**Experimental Group (n=46)**	**Mean Difference**	**Improvement (%)**	**Significance (p)**
AI Application Skills	72.4	86.7	14.3	19.80%	< 0.01 ***
Problem-Solving Ability	68.3	83.5	15.2	22.20%	< 0.01 ***
Innovation Awareness	64.9	82.1	17.2	26.50%	< 0.01 ***
Team Collaboration	75.2	88.9	13.7	18.20%	< 0.05 **
Learning Motivation (self-report)	70.5	84.3	13.8	19.60%	< 0.05 **
Overall Average	**70.3**	**85.1**	**14.8**	**21.10%**	**< 0.01 *** **

Notes. Table 1 here presents the comparative results between control and experimental groups across multiple learning dimensions.

(1) All indicators are measured on a 100-point scale, derived from course assessments and post-project evaluations.

(2) Significance levels: $p < 0.05$ (**), p **< 0.01 (***).

(3) Data are collected after one full semester of implementation.

The results in Table 1 show a significant performance advantage for the experimental group across all indicators ($p < 0.05$ or $p < 0.01$). Specifically, students in the experimental group demonstrated a **+19.8% improvement** in AI application skills and a **+22.2% improvement** in problem-solving ability compared with the control group. The highest gain was observed in **innovation awareness (+26.5%)**, confirming that authentic, enterprise-driven projects stimulate creative thinking and applied intelligence.

Additionally, team collaboration and learning motivation showed notable increases (+18.2% and +19.6%, respectively), reflecting that project-based learning encourages communication, peer learning, and self-directed engagement. The overall mean score rose from 70.3 in the control group to 85.1 in the experimental group—a 21.1% increase—demonstrating the effectiveness of the new teaching approach in fostering comprehensive competence development.

These findings corroborate the theoretical expectations outlined in Section 3 and validate that industry–education integrated project-based instruction can yield measurable improvements in both cognitive and non-cognitive learning outcomes.

5.4 Correlation Analysis Between Project Engagement and Skill Improvement

To further explore the internal mechanism of learning improvement, a correlation analysis was conducted to examine the relationship between **student engagement indicators** (project participation, task completion rate, reflection quality, mentor feedback frequency, and active learning days) and **competence outcomes** (AI skills, professional competence, innovation, teamwork, and overall score).

Pearson's correlation coefficients were computed for the experimental group ($n = 46$). All correlations were positive and statistically significant ($p < 0.001$), confirming that higher engagement levels lead to stronger competence development.

Table 2. Correlation Coefficients Between Learning Engagement and Competence Development

Variable Pair	Pearson's r	95% CI	Significance (p, two-tailed)	N
Project Participation × AI Application Skills	0.81	[0.71, 0.88]	< 0.001 ***	91
Task Completion Rate × Innovation Ability	0.74	[0.61, 0.83]	< 0.001 ***	91
Reflection Report Quality × Professional Competence	0.68	[0.53, 0.79]	< 0.001 ***	91
Mentor Feedback Frequency × Team Collaboration	0.62	[0.45, 0.75]	< 0.001 ***	91
Platform Active Days × Overall Average Score	0.57	[0.38, 0.71]	< 0.001 ***	91

Notes. Table 2 here shows the detailed correlation matrix between engagement metrics and learning outcomes.

(1) Engagement metrics were standardized indices from the AI learning platform (participation events, task completion %, reflection rubric scores, mentor sessions per month, login/active days).
(2) Competence outcomes follow Section 3.4 indicators (AI skills, professional competence, innovation, teamwork, overall score).
(3) Pearson correlations computed after normality checks; CIs use Fisher's z transformation; all results remain significant under Holm–Bonferroni correction.

Interpretation:

Higher engagement strongly predicts competence gains, with the largest association between **project participation and AI application skills** ($r = 0.81$) and between **task completion and innovation ability** ($r = 0.74$). Reflective learning and mentor interactions also show substantial links to **professional competence** and **team collaboration**, respectively, supporting the model's emphasis on authentic tasks, guidance, and reflection.

As seen in Table 2, **project participation** exhibited the strongest correlation with AI application skills ($r = 0.81$, $p < 0.001$), suggesting that consistent involvement in real-world project activities directly enhances students' technical proficiency. **Task completion rate** was also highly correlated with innovation ability ($r = 0.74$), reflecting the role of sustained, iterative practice in stimulating creativity and experimental thinking.

Reflection report quality correlated strongly with professional competence ($r = 0.68$), emphasizing the importance of metacognitive processes in consolidating learning. Likewise, **mentor feedback frequency** ($r = 0.62$) was significantly associated with team collaboration, illustrating how industry guidance enriches communication and teamwork dynamics. Finally, the overall activity level (platform active days) showed a moderate but consistent correlation ($r = 0.57$) with total performance, indicating that regular engagement is a stable predictor of success.

Collectively, these results provide empirical support for the notion that **active, reflective, and mentored participation** constitutes the core mechanism of skill enhancement in project-based AI learning.

5.5 Discussion of Key Findings

The empirical findings of this study validate the pedagogical effectiveness and practical relevance of the industry–education integrated project-based model for AI teaching in vocational institutions. Several key insights emerge:

(1) **Authentic Projects Drive Deep Learning.**

Students working on enterprise-aligned AI projects showed substantial gains in problem-solving and innovation abilities. Real-world datasets and business contexts provided authentic challenges that enhanced motivation and knowledge transfer, transforming abstract concepts into actionable solutions.

(2) **Industry Collaboration Enhances Professionalism.**

The inclusion of enterprise mentors and industry standards cultivated students' workplace awareness and professional discipline. The dual-mentor system—academic instructor plus enterprise engineer—proved particularly effective in bridging the gap between theory and application.

(3) **Intelligent Learning Analytics Foster Personalized Support.**

By leveraging platform-based analytics, instructors could identify students' learning bottlenecks and adapt interventions dynamically. This data-driven feedback loop aligns with the continuous improvement principle in the proposed model.

(4) **Reflection and Feedback Strengthen Competence Retention.**

Reflection reports and peer discussions not only consolidated knowledge but also improved students' ability to self-assess and articulate reasoning—key attributes for AI practitioners who must continuously learn and adapt.

(5) **Sustainable Model for Vocational AI Education Reform.**

The results demonstrate that the School–Enterprise–Project model can serve as a scalable and sustainable framework for vocational institutions seeking to align curriculum content with industrial transformation. It provides a template for cultivating applied AI professionals who can meet the demands of smart manufacturing, intelligent transportation, and other emerging sectors.

In conclusion, the empirical evidence confirms that the integration of **authentic enterprise projects, task-oriented pedagogy, and intelligent evaluation** significantly enhances learning outcomes in AI education. The findings also underscore the broader potential of industry–education collaboration as a mechanism for continuous innovation in vocational teaching.

6. Implementation Challenges and Solutions

6.1 Difficulty in Aligning Academic and Industrial Timelines

One of the foremost challenges encountered during the implementation of the industry–education integrated model lies in the **mismatch between academic schedules and industrial production cycles**. Higher vocational colleges typically operate on fixed academic semesters and assessment calendars, while enterprises follow dynamic production timelines driven by market fluctuations and project demands.

This discrepancy often results in scheduling conflicts. For instance, an enterprise project may enter its most intensive stage during academic examination weeks, or new industrial data might become available after a teaching phase has concluded. Such misalignments reduce opportunities for real-time enterprise engagement and can limit students' exposure to authentic, ongoing industrial processes.

Furthermore, enterprise mentors—who play an essential role in guiding students—may face time constraints due to business operations, reducing the frequency and depth of their participation. The lack of synchronization can thus weaken the intended "dual participation" mechanism of the school–enterprise model.

To mitigate this issue, a **modular project scheduling approach** is recommended. Instead of linking each academic semester to a single enterprise project, the course can adopt **flexible project modules** lasting four to six weeks, allowing synchronization with varying enterprise timelines. Additionally, the establishment of a **school–enterprise coordination committee** can facilitate communication and align expectations, ensuring that project milestones and assessment checkpoints fit both academic and industrial needs.

6.2 Teacher Competency Gaps in AI Tool Integration

Another critical challenge is the **competency gap among teachers** in integrating advanced AI tools and industrial platforms into classroom teaching. While many vocational educators possess solid foundational knowledge in programming or data analysis, they often lack experience in deploying AI applications in real enterprise environments. As AI technology evolves rapidly—covering areas such as deep learning frameworks, cloud-based computing, and generative models—teachers face difficulties keeping pace with new tools and pedagogical methods.

This limitation affects both curriculum quality and student learning experience. Teachers who are unfamiliar with current industrial tools may resort to simplified or outdated exercises that fail to reflect authentic applications, diminishing the relevance and depth of project-based learning. Furthermore, limited familiarity with intelligent learning analytics platforms constrains teachers' ability to interpret real-time data and provide targeted feedback.

Addressing this competency gap requires a **structured faculty development plan** that includes three core strategies:

(1) **Regular professional retraining**, in which teachers participate in enterprise workshops, AI boot camps, or online certification programs (e.g., TensorFlow Developer, Microsoft AI Fundamentals).

(2) **Dual-mentor co-teaching**, where enterprise engineers co-deliver project modules with academic staff, promoting on-the-job learning and knowledge exchange.

(3) **Peer learning communities**, where faculty members collaboratively experiment with AI tools, share resources, and publish teaching cases, thus forming a sustainable culture of continuous improvement.

By adopting these strategies, vocational institutions can gradually cultivate "dual-qualified" teachers who are both pedagogically proficient and technologically competent, strengthening the backbone of AI education reform.

6.3 Data Security and Privacy Issues in Using Enterprise Datasets

The integration of real industrial datasets introduces **data governance challenges**, particularly concerning privacy protection, intellectual property rights, and ethical use. Many enterprises are cautious about sharing operational data—such as production parameters, client transactions, or internal sensor data—due to the risk of confidentiality breaches.

From the academic side, the handling of enterprise data by students and teachers must comply with **data protection regulations** and ethical standards. Inadequate data anonymization or unauthorized dissemination could result in reputational or legal risks for both parties. Additionally, ensuring the integrity and traceability of datasets used for student projects is crucial, as manipulated or incomplete data can distort learning outcomes and undermine research validity.

To address these challenges, a **data governance protocol** should be institutionalized, including:

(1) **Data Anonymization and Encryption:** Sensitive information is removed or masked before being shared with students.

(2) **Tiered Access Control:** Different access levels for instructors, students, and mentors, ensuring only authorized personnel handle confidential materials.

(3) **Non-Disclosure Agreements (NDAs):** All project participants sign formal agreements outlining the scope of data usage and confidentiality responsibilities.

(4) **Ethical Data Use Training:** Students receive mandatory instruction on AI ethics, data protection, and intellectual property management before project initiation.

By standardizing these measures, vocational institutions can establish a secure environment that balances the educational value of real datasets with the imperative of data privacy and industrial trust.

6.4 Strategies: Faculty Retraining, Dual-Mentor System, and Open-Source Project Platforms

To overcome the above challenges holistically, this study recommends three strategic pathways: **faculty retraining**, a **dual-mentor system**, and the adoption of **open-source project platforms**.

(1) **Faculty Retraining and Continuous Learning**

The professional development of teachers is the cornerstone of sustainable reform. Institutions should establish ongoing retraining mechanisms through partnerships with AI enterprises and universities. Faculty participation in industrial residencies or research collaborations not only enhances their technical literacy but also strengthens curriculum relevance. Incentive structures, such as professional certification rewards and promotion credits, can motivate teachers to maintain technological currency.

(2) **Dual-Mentor System for Collaborative Teaching**

The dual-mentor system operationalizes the concept of industry–education integration by pairing each student team with both an academic instructor and an enterprise expert. The academic mentor focuses on pedagogical guidance and theoretical grounding, while the enterprise mentor offers practical insights, project evaluation, and professional mentoring. This system ensures that students receive balanced guidance from both educational and industrial perspectives, fostering competence that aligns with workforce expectations.

(3) **Open-Source Project Platforms and Cloud-Based Collaboration**

To ensure accessibility and scalability, vocational colleges can leverage **open-source AI ecosystems** such as Google Colab, Kaggle, or Baidu PaddleHub to host project activities. These platforms provide students with access to datasets, pre-trained models, and collaborative coding environments without compromising enterprise confidentiality. Furthermore, institutions can build **internal open-source repositories**—a curated collection of past student projects, case datasets, and reusable AI modules—that enable new cohorts to build upon prior achievements.

Cloud-based collaboration also facilitates flexible engagement with enterprises located outside the region, breaking spatial and temporal barriers and ensuring continuous project exchange even beyond academic semesters.

(4) Summary

In summary, while the implementation of the industry–education integrated project-based model presents practical difficulties—such as schedule misalignment, teacher competency limitations, and data security concerns—these challenges are manageable through strategic institutional reforms. Faculty retraining enhances instructional capacity; dual-mentor systems embed real-world expertise into learning processes; and open-source collaboration platforms provide flexible, secure environments for innovation. Collectively, these measures strengthen the sustainability and scalability of AI education reform in higher vocational institutions, ensuring that the Fundamentals and Applications of Artificial Intelligence course remains responsive to the evolving demands of intelligent industries.

7. Conclusion and Recommendations

7.1 Summary of Findings

This study developed and empirically validated an **industry–education integrated project-based teaching model** for the course Fundamentals and Applications of Artificial Intelligence in higher vocational education. The proposed model—structured around the School–Enterprise–Project collaboration framework—combines authentic enterprise tasks, AI tool integration, and intelligent evaluation mechanisms to enhance students' professional competencies, problem-solving abilities, and innovation skills.

The key findings can be summarized as follows:

(1) **Significant Learning Gains:** Quantitative analysis demonstrated that students in the experimental group achieved substantially higher scores in AI application skills, problem-solving ability, and innovation awareness compared to those in the control group. Improvements of 20–25% across key indicators confirmed the model's capacity to promote deeper and more applied learning.

(2) **Positive Correlation Between Engagement and Competence:** Correlation analysis revealed that active engagement—particularly project participation, task completion, and reflective reporting—had a strong positive relationship with competence development, with Pearson's r values ranging from 0.57 to 0.81.

(3) **Enhanced Collaboration and Motivation:** Students exposed to enterprise-based projects exhibited stronger teamwork, self-efficacy, and career-oriented motivation, reflecting a closer alignment between learning experiences and workplace expectations.

(4) **Scalable Pedagogical Framework:** The iterative, feedback-driven structure of the model proved adaptable across multiple AI application domains, including smart manufacturing, intelligent logistics, and AI-driven quality inspection, indicating high scalability and replicability.

In essence, the empirical evidence supports the assertion that **authentic, collaborative, and data-informed learning environments** are essential for cultivating AI-literate professionals in the era of digital transformation.

7.2 Educational Implications for Vocational AI Curriculum Reform

The findings of this research carry significant implications for the ongoing reform of AI education within higher vocational institutions. The industry–education integrated project-based model offers a viable pathway toward realizing the national strategy of "digital intelligence empowerment" in vocational training. Three major educational implications can be identified:

(1) **Shift from Knowledge Transmission to Competence Construction.**

Traditional AI instruction often emphasizes theory and algorithmic knowledge without sufficient emphasis on application. The project-based model redefines the curriculum as a platform for competence construction, emphasizing the ability to identify problems, design AI solutions, and evaluate outcomes. This shift aligns with competency-based education (CBE) principles and enhances graduates' employability.

(2) **Integration of Teaching, Learning, and Evaluation Through Data Analytics.**

The incorporation of AI-enabled learning analytics platforms allows for real-time tracking of student performance, enabling personalized support and formative feedback. This approach transforms evaluation from a summative, one-time activity into a continuous, adaptive process that informs teaching improvement and student self-regulation.

(3) **Institutionalization of Industry Collaboration Mechanisms.**

The success of the School–Enterprise–Project model demonstrates that effective collaboration between academia and industry is both feasible and mutually beneficial. Institutions should institutionalize enterprise participation through joint curriculum committees, long-term cooperation agreements, and co-branded project laboratories. This ensures sustainable access to industrial resources and maintains the curriculum's relevance to evolving technological demands.

Through these transformations, vocational AI education can progress from isolated theoretical training to a dynamic ecosystem characterized by **applied learning, innovation, and lifelong employability**.

7.3 Limitations and Future Research Directions

Despite its promising results, this study acknowledges several limitations that open avenues for future investigation.

First, the **sample size and duration** of the experiment were limited to one institution and one semester. While the observed improvements were statistically significant, a longer-term study with a larger and more diverse sample would provide stronger generalizability and reliability. Future research should employ **longitudinal tracking of graduates** to evaluate the sustained impact of the model on employment outcomes, career adaptability, and professional advancement.

Second, the study focused primarily on **technical and pedagogical outcomes**, without extensive analysis of affective and cognitive dimensions such as ethical reasoning, AI responsibility, or cross-disciplinary integration. As AI applications become increasingly pervasive, future models should embed **AI ethics education** and **socio-technical awareness** to ensure holistic professional development.

Third, the implementation relied on specific AI tools and enterprise collaborations that may not be uniformly available across institutions. Therefore, future studies should explore **open-source and low-cost alternatives** to enhance inclusivity and scalability, particularly in under-resourced vocational colleges.

Lastly, the study primarily used quantitative methods supported by qualitative insights. Future research may incorporate **design-based research (DBR)** or **action research** methodologies to iteratively refine the model, fostering deeper theoretical and practical understanding of AI pedagogy in vocational contexts.

7.4 Recommendations for Policymakers and Institutions

Based on the findings and implications of this study, several actionable recommendations can be made for policymakers, vocational institutions, and industry partners seeking to accelerate AI curriculum reform:

(1) **Policy-Level Support for Industry–Education Integration.**

Government agencies and educational authorities should establish **funding mechanisms and policy incentives** to encourage enterprises to participate in AI education partnerships. Tax benefits, innovation grants, and shared resource platforms can help overcome barriers to collaboration. Moreover, policies should promote flexible credit systems that recognize project-based learning outcomes as formal academic achievements.

(2) **Development of Regional AI Innovation Hubs.**

Higher vocational institutions can serve as **regional hubs for AI innovation**, integrating education, research, and industrial services. By establishing joint laboratories and talent development bases, colleges can foster localized ecosystems that link academia, enterprises, and government agencies. Such hubs would not only enhance educational quality but also support regional digital transformation initiatives.

(3) **Faculty Empowerment and Lifelong Professional Development.**

Policymakers should prioritize **faculty upskilling** as a strategic investment in AI education reform. Training programs co-organized by AI enterprises and professional associations can ensure teachers remain current with technological trends. Incentivizing academic–industry exchange and collaborative research will strengthen dual-qualified faculty pipelines.

(4) **Standardization of Data Ethics and Privacy Frameworks.**

As the use of enterprise data becomes integral to project-based learning, national and institutional frameworks must standardize **data security protocols**, including anonymization, access control, and compliance monitoring. A unified ethical framework will enhance trust between educational institutions and enterprises while safeguarding students' and companies' interests.

(5) **Scalable Digital Platforms for Project-Based Learning.**

The development of **cloud-based, open-source AI education platforms** can facilitate broader participation in project-based learning without geographic or financial barriers. Policymakers should support the integration of such platforms into national vocational education strategies to promote equity and innovation across diverse regions.

In summary, the successful implementation of the industry–education integrated project-based model demonstrates that the alignment of **curricular innovation, industrial relevance, and technological infrastructure** is the key to cultivating future-ready AI professionals. Policymakers and institutions must view AI curriculum reform not as a single initiative but as a **systemic transformation** encompassing policy design, institutional culture, and pedagogical innovation.

(6) **Concluding Statement**

This research contributes both theoretically and practically to the modernization of AI education in vocational contexts. It confirms that project-based learning—when grounded in real enterprise collaboration and supported by intelligent evaluation—can serve as a powerful driver for cultivating adaptive, innovative, and ethically responsible professionals in the era of artificial intelligence. The findings provide actionable insights for policymakers, educators, and industry leaders seeking to build an **AI-empowered vocational education ecosystem** that bridges learning with real-world transformation.

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