

# Research on Teaching Reform of Machine Learning Courses for Cultivating Engineering Innovation Capabilities

Xinan Chen, Jianzhong Li

*School of Computer Information Engineering, Hanshan Normal University, Chaozhou, Guangdong, China*

**Abstract:** The rapid evolution of artificial intelligence technologies and their deep integration with industry, university machine learning courses face entirely new demands for capability cultivation. Addressing the status quo where traditional teaching models lag behind the goals of training engineering innovation talents in terms of conceptual updates, content adaptation, and evaluation mechanisms, this study to address critical deficiencies—such as the disconnect between knowledge transmission and engineering practice, and the scarcity of student innovation capabilities. We constructed and implemented a "One Body, Two Wings" teaching reform scheme. This framework takes the systemic reconstruction of the Course Kernel (The Body) as the main component, enhancing teaching quality and efficiency in the teaching process through value reshaping, paradigm innovation, and the integration of application scenarios. It utilizes the collaborative support of Prerequisite and Parallel Courses (The Left Wing) to solidify mathematical foundations and create interdisciplinary practical contexts. Furthermore, it establishes a Subsequent Achievement Incubation Channel (The Right Wing) to build a diversified evaluation system and a value-added chain for capabilities. This framework constructs a complete cultivation ecosystem ranging from knowledge input and capability internalization to value output. Tracking data from two rounds of teaching practice indicate that this reform has achieved significant effectiveness in improving academic achievement, strengthening engineering practice capabilities, and cultivating comprehensive literacy, providing a referential practical paradigm for the construction of similar courses under the background of "New Engineering" education.

**Keywords:** Machine Learning; Engineering Innovation Capability; One Body, Two Wings; Teaching Reform; New Engineering Education

## 1. Introduction

The rapid evolution of artificial intelligence technology and its deep penetration into the industrial system are reshaping the capability structure and training objectives of engineering talents. As a key course in the construction of "New Engineering" disciplines and a vital carrier for AI talent training, the Machine Learning course is no longer limited to the transmission of algorithmic knowledge. Instead, it assumes the pivotal function of connecting frontier theories, complex engineering practices, and the cultivation of innovative problem-solving abilities [1]. The quality of course instruction and the effectiveness of reforms are directly related to whether universities can continuously output composite talents possessing systematic thinking, engineering practice capabilities, and cross-disciplinary integration skills.

However, current university machine learning courses face a systemic lack of adaptation in responding to these demands, primarily manifested as a disconnect in the "Teaching-Learning-Application" chain. First, course content lacks sufficient connection with industrial frontiers and real engineering scenarios, making it difficult to effectively stimulate learning motivation and professional value recognition[2]. Second, there is a distinct cognitive gap between mathematical foundations and algorithm applications, as well as between theoretical understanding and engineering implementation, leading to an absence of capability training[3]. Third, assessment methods dominated by summative examinations fail to effectively characterize and guide the formation of engineering innovation capabilities, resulting in a lack of traceable evidence for quality improvement[4]. The superposition of

these issues tends to trap students in a learning dilemma characterized by "shallow theoretical understanding, insufficient practical transfer, and weak innovation awareness," becoming a significant bottleneck restricting the quality of talent cultivation in New Engineering.

Although relevant studies have explored case-based teaching [5], experimental project optimization[6], and assessment reform [7], existing work mostly focuses on the implantation of single concepts (e.g., OBE, CDIO) or partial dimensional improvements (e.g., project practice, integration of science and education) [8-10]. It remains difficult to integrate the entire process of knowledge input, capability internalization, and value output. To this end, this paper proposes and practices a systemic teaching reform framework oriented towards engineering innovation capability cultivation, aiming to solve multiple disconnect issues through a structured scheme and verify its effectiveness through empirical data.

## **2. Status Quo and Problem Analysis of Machine Learning Course Teaching**

This study conducted a questionnaire survey on 180 undergraduate students majoring in Computer Science at a certain university who had completed the Machine Learning course, and conducted semi-structured interviews with 10 students of varying academic levels. The survey covered dimensions such as learning motivation, perception of course value, teaching satisfaction, and career development expectations, while interviews focused on the mechanisms behind the formation of problems. Based on the three levels of "Motivational Mechanism—Capability Construction—Quality Assurance and Development," the structural defects of the current teaching model were diagnosed.

### **2.1 Teaching Motivation Level: Insufficient Interaction and Weakened Endogenous Drive**

2.1.1 Low recognition of course value and insufficient alignment with professional capabilities

The survey shows a significant gap in students' recognition of course value. 64% of respondents believed the course had "excessive theoretical weight and limited direct contribution to job seeking," and 45.6% felt that "learning input did not match expected returns," leading them to turn to exam-oriented algorithm drills or

corporate internships. Interviews further indicated that the course's insufficient coverage of new engineering capabilities—such as model deployment, engineering toolchains, and AIGC-related applications—made it difficult for knowledge value to translate into perceptible professional competitiveness. Students were generally in a passive learning state, viewing the course merely as a task to earn credits rather than an opportunity to enhance engineering capabilities.

2.1.2 Rigid teaching models and lagging content updates

Course implementation remains dominated by "theoretical lectures + confirmatory experiments," characterized by a teacher-centered, one-way transmission approach with insufficient teacher-student interaction and learning community construction. Only 28.3% of students recognized the effectiveness of the existing model in stimulating interest, while 65.6% explicitly expressed a demand for case-driven, project-oriented, and inquiry-based learning. Simultaneously, the content update cycle lags behind technological evolution: 87.3% of students showed strong interest in Deep Learning and Large Language Models, but adjustments on the supply side of the course were insufficient to meet students' developmental learning needs.

### **2.2 Capability Construction Level: Disconnect Between Theory and Practice, Absence of Engineering Training**

2.2.1 Weak mathematical foundation support and cognitive fault lines

52.2% of students stated that their existing mathematical reserves were insufficient to support a deep understanding of complex algorithm principles. The reason is that prerequisite courses such as Calculus, Linear Algebra, and Probability & Statistics mostly adopt general education teaching styles, lacking coupling with machine learning problem contexts. This creates obstacles in "Math Tool—Algorithm Model" conversion, inhibiting the leap from symbol memorization to meaning construction.

2.2.2 Fragmented practice system and lack of cross-course synergy

Practical teaching suffers from both "insufficient training capacity" and "insufficient engineering authenticity." In terms of capacity, 16 credit hours of experiments struggle to support

full-process training from problem definition and data processing to model deployment. In terms of quality, experiments mostly remain at the level of standard dataset reproduction, lacking engineering experience in facing real data noise and business constraints. More critically, the course tends to form a "Knowledge Island," with insufficient synergy with parallel courses. Students rarely complete complex systems engineering problem-solving in cross-domain tasks, limiting the cultivation of systems thinking and transfer abilities.

### 2.3 Quality Assurance and Development Level: Deviated Evaluation Orientation and Insufficient Achievement Value-Added Channels

**2.3.1 Single evaluation mechanism and virtualized innovation capability orientation**  
The existing assessment system is dominated by final closed-book examinations (accounting for 70%), creating a "one exam determines the result" mentality. 68.9% of students believed that exam content lacked connection to engineering practice, and 53.3% admitted that their learning motivation was primarily "strategic test-taking." Elements reflecting higher-order literacy—such as project reports, algorithm implementation, teamwork, engineering specifications, and expression/communication—were not systematically included in the evaluation. Consequently, the assessment fails to effectively characterize capability development, nor does it provide sufficient data support for teaching improvement.

**2.3.2 Absence of development channels and solidified achievement value**  
The transformation of learning outcomes into high-level practices such as academic competitions, research training, or graduation theses lacks institutional articulation; course value often stops at the acquisition of a grade. In interviews, 7 students believed that course projects had the potential for deepening, but were shelved due to a lack of stable connection mechanisms with competitions and graduation projects. This not only causes a waste of educational resources but also blocks the path for the spiral ascent of innovation capabilities.

### 3. System Design of the "One Body, Two Wings" Teaching Reform Scheme

Addressing the aforementioned critical issues,

this study constructs a "One Body, Two Wings" reform framework (Figure 1) based on the Outcome-Based Education (OBE) philosophy. Through the organic coupling of the Body and the Two Wings, a closed-loop ecosystem of "Knowledge Internalization—Value Output" is formed.

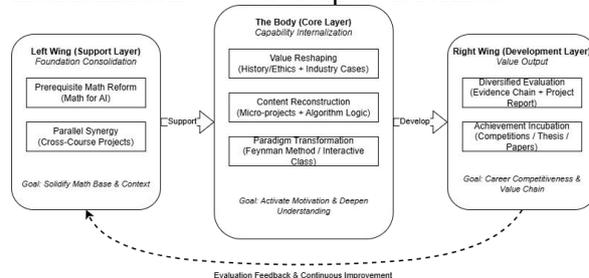


Figure 1. "One Body, Two Wings" Teaching Reform Framework

### 3.1 Overall Framework: Reform Topology with Synergistic Body and Wings

**The Body (Core Layer):** Systemic Reconstruction of the Course Kernel. As the central hub of reform, it focuses on the occurrence of learning and the generation of capabilities. Through value reshaping, content reconstruction, classroom paradigm transformation, and project-based learning organization, it promotes the internalization of knowledge understanding, engineering transfer, and innovative practice.

**The Left Wing (Support Layer):** Institutional Support from Prerequisite and Parallel Courses. As the cornerstone of capability, it aims to solve structural shortcomings. On one hand, it transforms prerequisite mathematical courses to bridge cognitive fault lines; on the other hand, it strengthens cross-course synergy to create comprehensive combat scenarios.

**The Right Wing (Development Layer):** Rear-Extended Achievement Channels. As the value-added orientation, it breaks the bottleneck of the disconnect between learning and application. By building an achievement incubation chain, it converts course outcomes into competition awards, papers, or software copyrights, achieving value externalization and sustainable development of professional competitiveness.

The three constitute a dynamic coupling closed loop: The Support Layer elevates the foundation, the Core Layer activates potential, and the Development Layer verifies effectiveness and feeds back to the front end, forming a self-evolving ecosystem.

### **3.2 Paradigm Transformation: Interactive Deep Inquiry**

3.2.1 Value reshaping: employment-innovation double helix content system

(1) Technological History & Ideological Integration and Ideological Integration: Tracing the development of machine learning, integrating the scientific historical context of key algorithm births and the exploratory spirit of scientists into teaching, achieving synergy between knowledge learning and the cultivation of scientific spirit.

(2) "Algorithmic Interview Questions—Industrial Cases" Dual-Track Resource Library: Systematically organizing algorithmic interview questions from top enterprises to directly address job-seeking core challenges; synchronously developing an industrial case library based on real datasets (e.g., Kaggle, Tianchi), such as credit default prediction and sensor fault detection, to present the engineering closed loop and reinforce professional value perception.

(3) "Empowerment-Type" Interdisciplinary Micro-Project Matrix: Designing "Machine Learning + X" micro-projects for core algorithms (e.g., Decision Tree + Medical Diagnosis, Clustering + Smart Transportation, Neural Networks + Text Style Transfer) to establish connections between algorithm principles and domain value, stimulating interdisciplinary imagination.

3.2.2 Paradigm transformation: interactive inquiry classroom and project-based learning organization

(1) Interactive Courseware Development: Developing interactive courseware based on Jupyter Notebook/Lab that integrates "theoretical explanation—formula derivation—code implementation—visualization analysis—parameter tuning" to replace traditional PPTs. This allows students to complete the inquiry cycle of "hypothesis—modification—verification—reflection" in a unified environment.

(2) Visualization Resource Fusion: Introducing resources like 3Blue1Brown and MLU-Explain to transform abstract concepts such as high-dimensional space projection and loss function surfaces into dynamic intuitive representations, reducing cognitive load and enhancing depth of understanding.

(3) Flipped Classroom and Role Transformation:

Recording basic theories into 10–15 minute micro-videos for pre-class study, reserving class time for project seminars, tackling difficulties, and roadshows. Teachers transform from "lecturers" to "learning architects, process guides, and engineering mentors," promoting the formation of higher-order thinking through problem chains and reflective questioning.

(4) Feynman Learning Method Driven "Dual-Path" Collaborative Inquiry Mechanism: To deepen knowledge internalization and cultivate teamwork and expression skills, two group collaboration tasks were designed. The outputs of these tasks serve as the core basis for the "Group Collaboration Performance" evaluation dimension.

Task 1: "Classic Decoding" Algorithm Science Popularization Project. Groups select a classic machine learning algorithm and cooperatively produce a popular science work (animation/interactive webpage) for a lay audience. Using the Feynman technique, groups clarify logic through discussion and explain core ideas using non-technical analogies ("teaching to learn"), thereby achieving deep internalization of knowledge.

Task 2: "Frontier Exploration" Industry Analysis Project. Groups act as "technical consultants," conducting in-depth research on the latest progress and commercial prospects of ML in vertical fields, producing structured industry analysis reports. This trains information retrieval, technological foresight, and academic expression capabilities.

The outputs of these tasks serve as important sources of evidence for subsequent diversified evaluation and reusable material for project incubation.

### **3.3 Support Layer Construction: Solidifying Math Foundations and Bridging Knowledge Application**

3.3.1 Bridging mathematical cognitive fault lines: prerequisite course modification and schedule optimization

(1) Adding "Mathematics for Artificial Intelligence" Prerequisite Course: Targeting the structural contradiction caused by weak math foundations, a new 64-hour compulsory course is added. It reconstructs core content of Linear Algebra, Probability Theory, Optimization Theory, and Information Theory from a Computer Science perspective. It adopts a logic of "reverse-engineering from algorithm

requirements to math tools" and configures Python programming practice to build a bridge between "abstract symbols" and "computational implementation."

(2) Rebalancing Credit Hour Structure: Compressing theoretical instruction from 32 to 16 hours and expanding experimental instruction from 16 to 32 hours, providing ample time for comprehensive project practice and cross-course collaboration. This "practical turn" reflects a capability-based value orientation.

3.3.2 Breaking course knowledge islands: creation of cross-disciplinary comprehensive combat projects

(1) Collaborative Teaching Teams: Forming a linkage team with the Capstone course offered in the same semester to jointly design project task books, share datasets, and conduct collaborative guidance.

(2) Co-construction of Typical Comprehensive Project Library: Building a cross-disciplinary project library, such as "Intelligent Detection of Network Anomalous Traffic" (merging ML and Network Security) and "Embedded Interaction System Based on Gesture Recognition" (merging Visual Recognition, Hardware Deployment, and System Design). This enhances systems thinking and cross-boundary integration capabilities through full-process training that approximates real systems engineering.

### 3.4. Development Layer Through-Put: Dual Channels for Quality Evaluation and Achievement Incubation

3.4.1 Diversified evaluation system: oriented towards engineering innovation capabilities

To correct the drawbacks of "one exam determines the result," this study builds a quality assurance system driven by diversified evaluation and evidence chains in the Right Wing to achieve a process that is "observable, quantifiable, traceable, and improvable."

(1) Reconstruction of Grade Structure: Adopting an evaluation model of "Theoretical Assessment (30%) + Comprehensive Project Report (30%) + Group Collaboration & Presentation (20%) + Chapter Assignments & Engineering Specifications (20%)," guiding students to shift from rote memorization to engineering capability construction.

Theoretical Assessment: Reducing memory-based questions; increasing algorithm design, complexity analysis, error diagnosis, and critical thinking questions.

Comprehensive Project Report: Focusing on problem definition quality, solution innovation, experiment reproducibility, result interpretation, and engineering standards.

Group Collaboration: Based on "Dual-Path" task outputs and roadshows.

Engineering Specifications: Emphasizing code style, documentation, version control, and experiment logs.

(2) Dynamic Assessment Content Mechanism: Establishing a question bank co-built by teachers and students, updated by approximately 30% each semester to ensure timeliness.

(3) Evaluation—Feedback—Improvement Loop: Using evaluation data to diagnose weak links, feeding back to content reconstruction in the Body and strengthening the Support Layer tools.

3.4.2 Achievement incubation chain: connecting "course—project—competition/thesis—transformation"

To solve the issue of broken achievement development channels, a "Three-Level Project" incubation system is constructed:

(1) Course-Level Project: Focusing on basic training of core algorithms and engineering implementation to form deliverable prototypes.

(2) Capstone-Level Project: Upgrading course team projects into cross-course comprehensive tasks.

(3) Graduation Thesis/Achievement Transformation: Supporting students in converting iterated projects into graduation thesis topics, extending to competition entries, software copyright applications, or deployable demos.

## 4. Evaluation of Reform Effectiveness and Reflection

To systematically evaluate the effectiveness of the "One Body, Two Wings" reform, this study tracked two rounds of teaching practice using mixed methods involving quantitative data and qualitative feedback to conduct an effectiveness assessment.

### 4.1 Teaching Motivation Dimension

Anonymous student ratings improved from the 64th percentile to the top 19th percentile (ranking). Online data showed video completion rates rose from 86.2% to 98.5%, and forum posts per capita increased from 1.3 to 8.7. The perception that the course was "very helpful" for career development rose from 45.2% to 79.8%.

#### 4.2 Knowledge and Capability Dimension

Through the incubation chain, 16 course projects were converted into graduation thesis topics, 4 theses received university-level excellence awards, and student works won 2 provincial-level or above competition awards.

#### 4.3 Comprehensive Literacy Dimension

Peer assessment showed an increase of over 35% in engineering literacy indicators like "code readability" and "documentation standardization." The "Dual-Path" mechanism significantly enhanced collaboration and professional communication.

#### 4.4 Reflection

There is room for optimization: (1) Institutional incentives for cross-course collaboration need strengthening (e.g., credit recognition); (2) The depth of frontier technology integration needs a sustainable modular content library; (3) Personalized learning support via AI-empowered diagnostics needs further exploration.

#### 5. Conclusion

Addressing the systemic "Teach-Learn-Apply" disconnect in Machine Learning courses within the New Engineering context, this paper constructed and empirically verified the "One Body, Two Wings" teaching reform framework. Practice demonstrates that the reconstruction of the Body promotes motivation and deep understanding; the mathematical reinforcement and synergy of the Left Wing provide necessary conditions for engineering innovation; and the Right Wing ensures continuous improvement and value externalization through diversified evaluation and incubation. Overall, this framework forms a closed-loop cultivation ecosystem of "Knowledge Input—Capability Internalization—Value Output—Evaluation Feedback," offering a reference for the systematic reform of similar courses.

#### Funding

This work was supported by the Teaching Reform Project of Hanshan Normal University (Grant No. HSJG-GK22645).

#### References

[1] Cong, S., Bao, P., Yuan, S., Ye, X., Liang, H.

(2022). Exploration and practice of collaborative innovation education mode in integration of science-education: Taking "Machine Learning" course as an example. *Theory and Practice of Innovation and Entrepreneurship*, 11(6), 7–10.

- [2] Chu, X., Wang, J., & Ding, X. (2024). Exploration of teaching reform for "Foundation of Machine Learning" course based on OBE concept. *Science and Education Guide*, 2024(3), 88–90.
- [3] Zhu, H., Liang, S., He, F., Li, H., & Xia, H. (2022). Exploration of machine learning course teaching based on project practice in the context of new engineering. *Guangxi Physics*, 43(2), 146–154.
- [4] Jiang, L., Zhang, L., Yan, J., & Wan, J. (2020). Teaching reform methods of machine learning's open practical course for undergraduate education. *Education Modernization*, 7(56), 76–79.
- [5] Yin, X., & Qian, Y. (2025). Teaching reform application practice of machine learning practice course driven by large model. *Software Guide*, 24(3), 206–210.
- [6] Wei, N., Yin, L., Ning, H., & Fang, B. (2022). Preliminary study on the reform of machine learning teaching. *Chinese Journal of Network and Information Security*, 8(4), 182–189.
- [7] Sun, J., Liu, S., Pang, C., Lei, X., & Sun, Z. (2024). Machine learning teaching reform for cultivating practice and innovation abilities. *Theory and Practice of Innovation and Entrepreneurship*, 12(6), 39–43.
- [8] Kang, Y., Wang, H., Tian, S., & Ren, K. (2023). Research on teaching and practice reform of machine learning course in ethnic colleges. *Education and Teaching Forum*, 2023(51), 89–92.
- [9] Liu, J., Wang, X., & Yuan, X. (2024). Exploration of teaching reform in postgraduate "Machine Learning" course based on CDIO concept. *Science and Education Guide*, 2024(19), 135–137.
- [10] Zhang, Z., He, W., & Wei, Y. (2025). LLM-driven tripartite curriculum reformation: Role, ecology, and personalized empowerment—Evidence from Introduction to Machine Learning. *Science and Education Guide*, 2025(18), 7–9.