

# From "Learning-Application Disconnect" to "Learning for Application": An Exploration of the Reform Path for General Artificial Intelligence Courses

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## Abstract

To address the "learning-application disconnect" in university general AI courses, this paper analyzes pain points such as outdated content, monotonous teaching methods, and wide disparities in students' foundations. It proposes a three-dimensional objective of "knowledge—ability—literacy" and three principles: "low code + high understanding," "scenario-based + project-based," and "disciplinary intersection." The reform path is explored through content reconstruction, blended teaching, and diversified assessment. Practice shows that course satisfaction rose from 80% to 97%, students' confidence in AI application increased from 54% to 89%, and the project completion rate reached 100%, providing a replicable paradigm for the inclusive development of general AI education.

## Keywords

AI courses; low code + high understanding; AI education.

## 1. Introduction

### 1. Research Background

At present, the strategic status of artificial intelligence has become a global consensus, and its development is strongly supported by national policies and driven by robust industrial demand. China's \*New Generation Artificial Intelligence Development Plan\* explicitly proposes elevating artificial intelligence to a national strategy<sup>[1]</sup>, and the Ministry of Education has simultaneously advanced the "AI+X" compound talent training program<sup>[2]</sup>. The policy orientation clearly requires universities to strengthen general artificial intelligence education and specialized construction. The explosive development of technologies such as large models and AIGC has further intensified the shortage of compound, application-oriented talent. Driven by both this strategic status and industrial demand, artificial intelligence education has become a core lever for the construction of new engineering disciplines.

Against this background, artificial intelligence education in universities is showing a trend of rapid popularization. On the one hand, the construction of "new engineering" requires breaking down disciplinary barriers and promoting the deep integration of computer science with medicine, finance, art, and other fields, cultivating interdisciplinary talent with "AI+X" capabilities; on the other hand, the learning demand for artificial intelligence among non-computer majors has surged. For example, economics and management majors need to master intelligent decision-making tools, and medical majors need to understand image recognition technology. The traditional "high-threshold" curriculum system oriented toward computer science majors can no longer meet diversified needs. However, the existing "Fundamentals of Artificial Intelligence" course faces severe challenges: teaching content is dominated by classical machine learning algorithms and mathematical derivations and fails to incorporate frontier technologies such as large models and AIGC in a timely manner; teaching methods rely excessively on theoretical lectures and code reproduction, and students lack opportunities for

practice in real scenarios; in addition, students differ significantly in programming foundations and disciplinary backgrounds, and the traditional "one-size-fits-all" teaching model leads to polarization in learning outcomes. These pain points severely constrain the improvement of the quality of general artificial intelligence education and the realization of talent training goals, and there is an urgent need to break through via curriculum reform.

## 2. Research Significance

Carrying out research on the reform of the "Fundamentals of Artificial Intelligence" course has important practical significance, and its core value is reflected at two levels. First, this curriculum reform research is a key practice responding to the national "AI+X" compound talent training strategy. As artificial intelligence technology penetrates deeply into fields such as healthcare, finance, manufacturing, and education, the state has clearly proposed cultivating interdisciplinary talent who understand both professional knowledge and AI tools. However, current artificial intelligence education in universities still suffers from problems such as "emphasizing technology over application" and "rigid disciplinary barriers," resulting in a mismatch between talent supply and industrial demand. By incorporating interdisciplinary cases such as medical image analysis and financial risk prediction, this curriculum reform constructs a teaching framework of "AI + domain knowledge," which can directly serve national strategic needs and deliver compound talent with AI application capabilities to emerging industries.

Second, this curriculum reform research is committed to solving long-standing bottlenecks in traditional teaching. Existing curriculum systems generally show a tendency to "emphasize theory over practice," focusing excessively on algorithm derivation and mathematical proof. Although students can understand model principles, they cannot transform them into the ability to solve practical problems. At the same time, teaching content updates lag behind technological development, and frontier technologies such as large models and AIGC have not yet been incorporated into the teaching system, causing graduates' knowledge structures to become disconnected from industry needs. By introducing AutoML tools to lower programming thresholds, adopting enterprise real-scenario project-driven learning, and establishing a dynamically updated content mechanism, curriculum reform can effectively bridge the "learning-application gap" and improve the timeliness and practicality of talent training.

## 2. Analysis of the Current Course Status and Motivations for Reform

### 1. Analysis of the Existing Curriculum System

In terms of teaching methods, the course still adopts a passive learning model of "one-way teacher lecturing + after-class assignment consolidation," and the problem of simplistic experimental design is prominent. Because textbooks are biased toward theory and the experimental environment is limited, students cannot personally complete artificial intelligence projects during instruction and can only consolidate through related assignments. This kind of "armchair strategizing" training means that although students can complete classroom exercises, they cannot apply technology to actual projects, further exacerbating the "learning-application disconnect."

The pain points in teaching effectiveness are concentrated in the "three difficulties dilemma" reported by students—obscure formula derivations lead to difficulty in theoretical understanding, complex programming tasks trigger fear of difficulty, and abstract application scenarios cause loss of goals. A questionnaire survey shows that 78% of students believe that "a weak mathematics foundation constrains interest in learning AI," 65% of students state that "experimental content is vaguely related to future careers," and 42% of non-computer majors have considered giving up because of the "excessively high code threshold"<sup>[3]</sup>. This learning experience of low participation and weak sense of achievement ultimately leads to a serious

deviation between course objectives and expected talent training outcomes, and systematic reform is urgently needed to break through and achieve renewal.

## 2. Analysis of Motivations for Reform

At present, the urgency of reforming the "Fundamentals of Artificial Intelligence" course stems from the triple drivers of technological iteration, student development needs, and industrial transformation. From the technological perspective, disruptive technologies represented by large language models and AIGC are reconstructing the field of artificial intelligence at exponential speed. Breakthroughs such as the emergent capabilities of the GPT series models, cross-modal generation by Stable Diffusion, and the perception-decision integration of multimodal large models have gradually reduced classical algorithms such as decision trees and support vector machines, which once dominated traditional courses, to "basic components" in the technology map. However, existing teaching content still focuses on the algorithmic framework from a decade ago and fails to cover frontier knowledge such as the Transformer architecture, attention mechanisms, and Prompt Engineering, resulting in a 3–5 year generational gap between what students learn and mainstream industry technologies, creating the awkward situation of "falling behind as soon as learning is completed."

From the perspective of students' personal development needs, the structural contradictions in the post-pandemic job market further amplify the necessity of curriculum reform. The combined effect of downward pressure on the global economy and the replacement of traditional jobs by artificial intelligence has made "technological empowerment" a key bargaining chip for improving employment competitiveness. A McKinsey Global Institute report shows that by 2030, 220 million workers in China will need to switch career tracks, among which the demand growth rate for compound talent with AI tool application capabilities will reach 34%. However, students trained by the current curriculum can only complete basic work such as algorithm reproduction and lack the ability to apply AI technology to specific industry scenarios, making it difficult to meet the market's urgent demand for "AI practitioners who understand business logic."

## 3. Curriculum Reform Objectives and Design Principles

### 1. Reform Objectives

This reform of the "Fundamentals of Artificial Intelligence" course establishes a three-dimensional integrated objective system, aiming to build a general AI education paradigm that meets the needs of the times. At the knowledge objective level, the course breaks through the traditional single framework centered on algorithms and shifts to an integrated design of "foundational theory + frontier vision." Students must not only master the basic principles of machine learning, typical deep learning architectures (such as CNN/RNN), and core concepts of large models (such as attention mechanisms and context windows), but also understand the applicable boundaries and limitations of each technology. For example, by comparing the accuracy and computational cost of traditional algorithms and large models in medical image diagnosis, students are helped to establish dialectical thinking that "there is no optimal technology, only the most suitable solution," thereby cultivating the ability to accurately judge technology application scenarios.

The ability objective focuses on the coordinated development of three core competencies: first, cultivating data-driven problem-solving thinking, enabling students to extract features from massive information and construct models; second, strengthening tool invocation and resource integration capabilities, allowing students to master the practical skills of "deploying AI solutions without programming from scratch" through practice with AutoML platforms, low-code development environments, and other tools; third, enhancing scenario-based application ability, guiding students to transform AI technology into the ability to solve specific problems

in healthcare, finance, education, and other fields. For example, in the "e-commerce promotion strategy optimization" project, students need to comprehensively use tools such as cluster analysis and time-series forecasting to complete the entire process from data cleaning to decision recommendations.

The literacy objective focuses on cultivating ethical responsibility and collaborative awareness in the age of artificial intelligence. The course integrates an AI ethics module throughout, guiding students to think deeply about the value choices behind technology by analyzing social cases such as "algorithmic recommendation leading to information cocoons" and "facial recognition violating privacy" [6]; at the same time, it sets interdisciplinary collaborative tasks (such as a medicine + AI group developing an auxiliary diagnostic tool) to break down professional barriers and forge communication, coordination, and resource integration capabilities. This objective system of "knowledge as foundation—ability as empowerment—literacy as soul" aims to cultivate compound AI application talent who understand both technological boundaries and possess humanistic care.

## 2. Design Principles

This curriculum reform follows three core design principles, aiming to build a new AI education paradigm that conforms to the cognitive patterns of non-computer majors and fits industrial needs. The first principle is "low code + high understanding." In response to the "fear of difficulty" and "learning-application disconnect" caused by excessively high programming thresholds in traditional teaching, it proposes a solution of "tool empowerment, thinking first." By introducing AutoML automated machine learning platforms (such as Google Cloud AutoML) and interactive visualization tools (such as Microsoft Azure ML Studio), students are liberated from cumbersome code writing and instead focus on higher-level decision-making questions such as "why choose a specific AI technology" and "how to evaluate model applicability"[4]. For example, in a medical image classification project, students can complete data annotation, model training, and parameter tuning by dragging and dropping components, while deeply understanding the advantages and limitations of CNN algorithms in medical image processing, achieving the teaching breakthrough that "AI can be done even with zero foundation."

The second principle is "scenario-based + project-based," emphasizing knowledge construction driven by real industry needs. The course abandons abstract cases detached from reality and instead uses typical scenarios in healthcare, finance, retail, and other fields as teaching carriers: in the medical module, students need to analyze real X-ray datasets and build auxiliary diagnostic models; in the e-commerce scenario, they design personalized recommendation systems by analyzing user behavior logs; and for financial risk control needs, they use time-series forecasting technology to build credit default warning models. Each project includes the full process of "business problem definition—data feature engineering—model selection and evaluation—application effect analysis," enabling students to naturally master the implementation methodology of AI technology while solving complex problems.

The third principle is "disciplinary intersection," breaking the mindset of traditional engineering education and practicing the "AI+X" interdisciplinary integration concept. The course content deeply integrates diverse domain cases such as medical image analysis (such as tumor recognition), financial quantitative trading (such as risk control models), and artistic creation assistance (such as AI painting style transfer), guiding students to explore the application potential of AI from different disciplinary perspectives. This cross-boundary design not only broadens students' horizons but also cultivates their comprehensive ability to transform AI technology into solutions for vertical domains, truly achieving the educational goal of "technology as foundation, scenario as king, innovation-driven."

## 4. Specific Content and Implementation Paths of Curriculum Reform

### (1) Reconstruction of Teaching Content: From "Algorithm-Centered" to "Scenario-Driven"

#### 1. Modularized Knowledge System

This curriculum reform constructs a four-dimensional integrated modularized knowledge system, achieving a structural reconstruction of artificial intelligence education content through systematic layered design. As the cornerstone of cognition, the basic module breaks through the single technology-oriented perspective and takes the history of artificial intelligence development and technological boundaries as its opening content. It analyzes the logic of technological evolution through milestone events such as the Turing Test and AlphaGo, and combines discussion of the current limitations of AI in areas such as common-sense reasoning and causal inference to help students establish an objective framework of technological cognition; it simultaneously embeds an AI ethics and safety module, using real cases such as medical diagnostic bias and algorithmic employment discrimination to guide students to reflect on the social responsibility behind technology, cultivating AI thinking that combines technical literacy and humanistic care from the starting point.

The core module adopts a dual-track design of "conceptual framework + technological foresight," both consolidating the basic theory of machine learning (classification/regression tasks in supervised learning, clustering algorithms in unsupervised learning) and prospectively introducing core deep learning architectures (the application logic of convolutional neural networks, CNN, in image processing; the time-series modeling principles of recurrent neural networks, RNN) and large model application paradigms (strategy design for prompt engineering, Prompt Design; standardized processes for API invocation interfaces). This knowledge arrangement from shallow to deep avoids falling into the quagmire of complex formula derivation while ensuring that students can grasp the trajectory of technological evolution.

The innovation of the tool module is embodied in the deconstruction and reshaping of traditional programming ability. Through streamlined Python syntax teaching (focusing on high-frequency operations such as Pandas data processing and Matplotlib visualization), combined with AutoML tools (zero-code model training with Google AutoML, automated feature engineering with DataRobot) and low-code platforms (drag-and-drop modeling with Azure ML Studio), it builds a three-level capability ladder of "basic programming → intelligent tools → visual development," enabling students to flexibly choose technical paths according to their own foundations.

As the practical carrier of the knowledge system, the scenario module selects three typical fields: medical image recognition (early lung cancer screening), financial risk control models (credit default prediction), and educational personalized recommendation (adaptive learning systems). Each scenario is equipped with simplified practical projects, and through real dataset operations and business process simulation, it helps students establish a global mindset of "from scenario pain point analysis to AI solution design," truly achieving learning for application.

#### 2. Content Update Mechanism

To ensure the frontier nature and industry adaptability of course content, this course constructs a dynamic and sustainable content update mechanism, forming a dual-wheel-driven model of "frontier tracking—school-enterprise collaboration." At the level of technological iteration, the course establishes a "frontier topics" module, dynamically embedding 20% of the latest research results and industrial breakthroughs each semester. Specifically, it offers thematic seminars around the technical principles and application scenarios of generative artificial intelligence (AIGC), analyzing the innovative application of diffusion models (Diffusion

Model) in image generation and the in-context learning mechanism of large language models (LLM); it simultaneously tracks the development trends of multimodal large models, discussing the principles of the CLIP model in achieving image-text cross-modal alignment and the architectural breakthroughs of Sora video generation technology. By inviting enterprise engineers to give technical lectures and organizing students to study arXiv preprint papers, frontier knowledge such as the evolution of the Transformer architecture and the optimization of attention mechanisms is integrated into teaching, ensuring that the industry cognition students are exposed to remains at the forefront of the technology development curve.

## (2) Innovation of Teaching Methods: From "One-Way Lecturing" to "Multiple Interaction"

### 1. Blended Teaching Model

To break the teaching dilemma of traditional classrooms characterized by "one-way indoctrination and insufficient practice," this course constructs a blended teaching model of "flipped classroom + project-based learning (PBL)"<sup>[5]</sup>, achieving a leap from knowledge transmission to ability cultivation by reconstructing the teaching process. In the pre-class preparation stage, basic knowledge transmission is completed through carefully designed 5–10 minute micro-lecture videos. These short videos adopt a three-stage structure of "problem introduction—core explanation—case verification." For example, in the "Fundamentals of Machine Learning" unit, the concept of supervised learning is introduced through the question "How can computers recognize handwritten digits?", the MNIST dataset annotation process is demonstrated with animation, and finally the algorithm effect is verified with a Scikit-learn invocation case. Students can watch repeatedly at their own pace and test their preview effectiveness through online quizzes, laying a cognitive foundation for classroom discussion.

The in-class segment focuses on the cultivation of higher-order thinking training and collaborative problem-solving ability. Teachers design driving questions around real scenarios (such as "Using AI to optimize campus express locker layout" and "Designing a library seat reservation system"), guiding students to conduct group discussions. In the process, teachers no longer directly impart knowledge but instead inspire technology selection ideas through questioning (such as "Does this problem require real-time response?" and "Is the cost of data acquisition controllable?"), assisting students in sorting out logical frameworks (such as decomposing the express locker optimization problem into three-level subtasks: "pedestrian flow prediction → locker allocation → dynamic scheduling"). This model of "teachers setting the stage, students performing" prompts students to actively use the knowledge learned before class to propose solutions and deepen their understanding of technological boundaries and application scenarios through collisions of viewpoints.

After-class practice achieves knowledge transfer and ability consolidation through mini-projects. Each group must complete the full process from problem definition to result analysis within two weeks. For example, when using the AutoML platform to train a garbage classification model, students must independently complete tasks such as data cleaning (handling image noise and annotation errors), feature engineering (extracting color histograms and texture features), and model parameter tuning (choosing ResNet or MobileNet architectures), and write a summary report including accuracy comparison and misclassification case analysis. This "learning by doing" model not only improves students' tool application ability but also cultivates their systematic thinking and project management ability when facing complex problems.

### 2. Empowerment by Digital Tools

To improve teaching interactivity and experimental accessibility, this course deeply integrates digital tools to build an intelligent and immersive learning environment. In the classroom teaching segment, Jupyter Notebook is fully adopted as the core teaching carrier, and an interactive teaching model of "writing code while explaining" is innovatively implemented.

When explaining machine learning algorithms, teachers are no longer limited to static PPT demonstrations but write Python code in real time (such as the random forest parameter tuning process in Scikit-learn). By dynamically displaying key steps such as data preprocessing (missing value imputation, feature standardization), model training (calling the fit method), and evaluation metric calculation (accuracy\_score output), abstract theoretical knowledge is transformed into intuitive visual results. Students can simultaneously operate their personal devices to follow along and practice, and by inserting cells to try modifying hyperparameters (such as adjusting the n\_estimators value), they can immediately observe changes in model performance. This "hands-on and mind-on" learning method significantly improves the efficiency of knowledge internalization.

### (3) Reform of Assessment Methods: From "Result Evaluation" to "Process Value-Added"

To build a comprehensive and objective evaluation mechanism for learning outcomes, this course innovatively adopts a diversified assessment system combining "process evaluation and summative evaluation," focusing on students' comprehensive performance in knowledge application, collaborative innovation, and higher-order thinking. In terms of process evaluation, three progressive assessment indicators are set up, forming a full-cycle monitoring network of "daily accumulation—classroom interaction—project practice." Among them, assignments account for 15%, focusing on the understanding and application of basic knowledge, such as testing data preprocessing ability through Python programming problems (such as missing value imputation and feature normalization), or requiring students to use visualization tools to draw decision tree branching logic, ensuring solid mastery of theoretical knowledge. Classroom discussion contribution accounts for 20%, using a two-dimensional scoring standard of "speech quality + collaboration effectiveness," encouraging students to put forward innovative viewpoints (such as debating "the ethical boundaries of AI in medical diagnosis") or integrating group discussion results through mind-mapping tools, cultivating knowledge integration and communication expression ability. Group projects account for 25%, focusing on examining solution creativity (such as introducing a dynamic weighting algorithm in campus express locker layout optimization) and implementation effects (quantitative indicators such as model accuracy and system response speed). Students are required to submit a complete report including problem definition, technology selection, and result analysis, and display project highlights and improvement directions through defense. This process evaluation design not only covers multiple ability dimensions such as knowledge mastery, skill application, and teamwork, but also helps students adjust learning strategies in a timely manner through staged feedback mechanisms.

Summative evaluation adopts an open-book examination format, accounting for 40%, focusing on examining students' comprehensive application and analytical ability regarding knowledge. The examination questions break through traditional memory-based items and focus on technical decision-making problems in real scenarios. For example: "When inputting a  $32 \times 32 \times 3$  RGB image, after passing through a CNN containing two  $3 \times 3$  convolution kernels (stride 1, padding 1) and one  $2 \times 2$  max pooling layer (stride 2), what is the size of the output feature map?" Such questions require students to derive based on understanding the principles of convolution operations, combined with formula calculation and the rules of spatial dimension changes, effectively distinguishing the learning effects of "rote memorization" and "true understanding." In addition, the examination adds case analysis questions (such as "Possible reasons and improvement measures for a decline in the click-through rate of an e-commerce recommendation system"), guiding students to use the recommendation algorithm principles and evaluation indicators learned in the course for logical reasoning, further strengthening problem-solving ability. This evaluation system of "process emphasizing ability, summative emphasizing thinking" realizes all-round and multi-level consideration of student learning outcomes [7].

## 5. Reform Effectiveness

The effect evaluation after the implementation of the curriculum reform shows that students have made significant progress in learning experience, practical ability, and academic application. In terms of course satisfaction, an anonymous questionnaire survey found that students' overall evaluation of the course rose significantly from 80% before the reform to 97%, among which the three indicators of "practicality of teaching content," "interest of classroom interaction," and "effectiveness of project guidance" showed the most significant increases. The keywords appearing frequently in student feedback include "cases close to reality" (68%), "tools lower the AI threshold" (75%), and "great gains from group cooperation" (82%), indicating that the reconstructed modularized knowledge system and project-driven teaching model effectively stimulated learning interest. More breakthrough, a special survey on "confidence in AI application" showed that the proportion of students who believed that "I can apply AI technology in future work" jumped from 54% to 89%, reflecting that "low-code tool empowerment" and "scenario-based project practice" significantly reduced non-computer majors' fear of technology.

In terms of ability improvement, the reform effectiveness has also been verified by data. The group project completion rate increased from the historical average of 70% to 100%, and project quality improved significantly—85% of groups were able to independently complete the full process from problem definition to model deployment. Some excellent projects (such as an AutoML-based campus garbage classification system and an LSTM-integrated library seat prediction model) were recommended to participate in university-level innovation and entrepreneurship competitions and won awards. More noteworthy is that the long-term impact of the course on students' academic research has gradually emerged: in recent undergraduate thesis topic selections, the proportion of theses involving artificial intelligence algorithm applications increased from 12% before the reform to 34%. A typical case is that a student majoring in economics and management applied the Dijkstra algorithm (suitable for single-source shortest path search in static environments) to urban logistics distribution route optimization, constructed a graph structure model by calling the NetworkX library in Python, and verified the algorithm's effectiveness in reducing distribution costs using real traffic data. This ability transfer "from classroom projects to academic research" fully proves the sustainable effectiveness of curriculum reform in cultivating students' "learning for application" ability.

## 6. Reflection and Directions for Continuous Improvement

### 1. Existing Problems

While the curriculum reform has achieved phased results, there are still two problems that need to be solved urgently. First, some students show a phenomenon of "tool dependence," overly relying on automated tools such as AutoML while neglecting understanding of underlying principles. The specific manifestations are: in group projects, students can skillfully use the platform to complete model training and parameter tuning, but when asked theoretical questions such as "why choose a specific algorithm" and "how feature engineering affects results," most can only give vague answers; in the final examination, the loss rate on questions involving algorithm logic derivation (such as the feature extraction principle of convolutional neural networks) is as high as 42%. This reflects that while "low-code teaching" lowers the entry threshold, it may lead students into the dilemma of "knowing the result but not the reason." This needs to be balanced by adding "principle exploration" segments (such as using visualization tools to disassemble the neural network decision-making process). Second, the matching degree between enterprise cases and teaching needs still needs improvement. Although cases such as e-commerce recommendation systems and medical image classification

have been introduced, some scenarios (such as real-time anti-fraud models in financial risk control) can only display simplified processes due to data security restrictions, making it difficult for students to deeply understand technology selection and deployment strategies under complex business logic. In addition, the update speed of cases in emerging fields (such as AIGC content generation and multimodal large model applications) has not fully kept up with the pace of industrial iteration. In the future, it is necessary to continuously optimize the connection between teaching content and industrial needs by deepening school-enterprise cooperation and establishing a dynamic case library.

## 2. Improvement Plan

In response to the "tool dependence" problem exposed in curriculum reform, a targeted improvement plan is now formulated. The primary measure is to add a "principle exploration" teaching segment, revealing the core logic behind technology through visualization tools and interactive experiments, helping students deepen theoretical cognition in application practice. Specifically, in the neural network module, three-dimensional visualization tools such as TensorSpace are introduced to dynamically display the entire process of convolutional layers extracting image edge features, pooling layers compressing data dimensions, and fully connected layers integrating semantic information, enabling students to intuitively understand the internal mechanisms of "feature abstraction" and "decision boundary formation." For decision tree algorithms, an interactive decision path simulator is developed, allowing students to observe changes in classification rules by adjusting feature thresholds and comprehend the balance between information gain and overfitting risk. At the same time, an additional "principle explanation" question (accounting for 10%) is added to course assessment. Students are required, when submitting project reports, to attach technology selection justification (such as "why random forest was chosen instead of SVM to handle high-dimensional sparse data") and algorithm limitation analysis (such as "the robustness defect of the current model under noisy data"). In addition, a "counterfactual case" teaching method is planned—comparing and displaying the decision differences of different algorithms in the same scenario (such as the interpretation of medical image misjudgment cases by decision trees and neural networks), guiding students to reflect on the boundary conditions of tool application. These improvements will build a closed-loop learning chain of "tool application—principle exploration—critical reflection," fundamentally solving the teaching pain point of "knowing the result but not the reason."

## 7. Conclusion

The innovation of curriculum reform is reflected in three aspects: first, scenario-based teaching drives learning through real industry cases (medical image classification, e-commerce recommendation systems), enabling students to understand AI technology in specific business scenarios and avoiding the sense of fragmentation of "learning technology for technology's sake"; second, the introduction of low-code tools (such as AutoML platforms and visual modeling tools) greatly lowers the programming threshold, allowing students to focus on "how to use AI to solve problems" rather than "how to write code," effectively bridging the skill gap of non-computer majors; third, interdisciplinary integration incorporates actual needs from medicine, finance, art, and other fields into teaching, embodying the "AI+X" compound talent training concept and broadening students' application horizons.

The promotion value of this model lies in that it provides a replicable paradigm for general artificial intelligence education for non-computer majors—reducing learning resistance through "low-threshold tools + high-empowerment scenarios," improving application ability through "interdisciplinary cases + project-based practice," and enabling students from more

majors to master the basic logic and application methods of AI technology, meeting the demand for compound talent in the digital economy era.

In terms of future prospects, the deep integration of "AI + education" will further promote curriculum upgrading. For example, introducing AI teaching assistants to achieve 24-hour intelligent Q&A and personalized learning feedback, and using learning behavior data analysis to recommend customized learning paths for students (such as pushing visual analysis resources to "theory-weak" students and recommending advanced project cases to "practice-deficient" students); exploring virtual digital humans to simulate the role of industry experts and enhance the authenticity of classroom interaction; and combining large model technology to build a dynamic knowledge base to achieve real-time updates and personalized推送 of teaching content. These innovations will further improve teaching efficiency and learning experience, providing new ideas for the inclusive and intelligent development of artificial intelligence education.

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