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Exploration and Practice of Teaching Reform in the Course of Introduction to Artificial Intelligence Based on Knowledge Graph

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Abstract: The current course "Introduction to Artificial Intelligence" is facing problems such as knowledge connections being fragmented by chapters, significant differences in starting points among students from multiple majors, experimental bias towards verification, and a lack of process data in the final evaluation. This article takes the curriculum knowledge graph as the core to promote teaching reform. The graph is constructed according to four levels of "course knowledge unit knowledge domain knowledge point", defining five types of relationships: predecessor, successor, inclusion, intersection, and application, and linking resources such as courseware, code, and datasets to knowledge points. Teaching is divided into three stages: pre class guidance, in class intensive lectures, and post class expansion. Graph plays a role in navigation and recording learning behavior. Evaluation is based on node mastery, combined with teacher evaluation, student self-evaluation, and group peer evaluation. The plan will be implemented in the second semester of the 2025-2026 academic year at the School of Information Engineering of Nanjing Xiaozhuang University, with 196 students enrolled. The results showed that teaching, practice, and diagnosis share the same knowledge structure, and classroom time has shifted from being evenly distributed to being allocated based on error rates. Teacher intervention can be targeted to specific knowledge points. This model does not rely on commercial platforms and can be used as a reference for structured teaching transformation of similar courses.

Keywords: Introduction to Artificial Intelligence; Course Knowledge Graph; Learning Path; Process Evaluation; Teaching Reform

1. Introduction

In April 2025, the Ministry of Education and nine other departments issued the "Opinions on Accelerating the Digitalization of Education", requiring the improvement of knowledge graphs and the construction of ability graphs, and promoting the intelligent upgrading of curriculum systems, textbook systems, and teaching systems. Previously, the "Development Plan for the New Generation of Artificial Intelligence" had listed intelligent education as a key application direction, and the "Action Plan for Artificial Intelligence Innovation in Higher Education Institutions" called for accelerating the construction of courses and talent training systems in the field of artificial intelligence. The implementation path at the course level is clear: first organize the course content into a machine-readable and navigable structure, and then discuss personalized teaching.

The demand for structured content in Introduction to Artificial Intelligence is more urgent. The course is offered to multiple majors with limited class hours, covering eight modules including Introduction to Artificial Intelligence, Knowledge Representation, Search Reasoning, Machine Learning, Deep Learning, Computer Vision, Natural Language Processing, and Intelligent Ethics. There are two types of connections between these modules that cannot be omitted. One is predecessor dependency, for example, gradient propagation of loss function is a prerequisite for backpropagation algorithm. After separating the two, backpropagation can only be remembered as a "black box". The second is cross reuse, such as attention mechanism supporting both machine translation and image recognition, semantic network and knowledge graph sharing the modeling idea of "node edge". The order of textbook chapters cannot present these two types of connections,

and students receive isolated definitions rather than usable structures. In addition, there is a significant difference between the programming and mathematical foundations of the students taking the course. The uniform progress causes the weak to continue owing debts, while those with a foundation repeat known content. The experimental stage stops at reproducing single algorithms, and the assessment focuses more on conceptual memory. Teachers cannot obtain fine-grained learning data, and intervention can only stay at a general level.

Knowledge graph represents knowledge points with nodes and relationships with semantic edges, and can organize courses into a searchable and navigable network. Its construction technology and application have been systematically studied [1-4], and it has been used in the field of education for adaptive learning path recommendation [5]. It has also been used for content organization in courses such as power electronics technology [6], PLC principles and applications [7], and computer networks [8]. On this basis, this article solves two problems. One is to provide the construction method and classroom usage of the knowledge graph for the course "Introduction to Artificial Intelligence". The other is to test the practical role of the graph in knowledge organization, path navigation, and process evaluation during a semester of 196 course selections.

2. Current Situation and Problems of Course Teaching

2.1 Knowledge Association is Fragmented by Linear Teaching

There are numerous correlations within and between the eight modules of the course. In the machine learning module, the differences between supervised, unsupervised, and reinforcement learning lie in problem setting and evaluation methods, which is a horizontal connection. In the deep learning module, the perceptron, activation function, loss function, gradient descent, backpropagation, and convolutional neural network form a strict precursor chain, which is a vertical connection. Traditional teaching progresses section by section according to the textbook, with the precursor chain fragmented into independent lessons that appear in sequence, and horizontal connections falling outside the boundaries of the chapters. Students can repeat 'gradient descent updates parameters along the negative gradient direction', but cannot answer 'what does the loss function provide for gradient descent' because the two are separated by a chapter in the textbook. Comprehensive tasks require students to retrieve and assemble knowledge from multiple modules, while knowledge stored in isolation cannot be retrieved. The root of the problem lies not in the teacher's teaching level, but in the lack of an explicit carrier to express the relationship between knowledge points.

2.2 Conflict between Unified Progress and Differentiated Starting Point

Among the students taking courses, computer science majors have a foundation in programming and algorithms, while students from other majors have shortcomings in the linear algebra section of advanced mathematics and Python programming. Some universities have designated this course as a public course, further amplifying the differences in starting points. Unified progress transforms starting point differences into polarization: weak learners are forced to follow up without prior knowledge, and each class adds new cognitive gaps on top of them; Students with a foundation repeat known content, and the marginal benefit of classroom time tends to be zero. Layered teaching requires two conditions: data that can determine an individual's current mastery status, and a mechanism that can generate different paths based on the status. Traditional classrooms lack both, and stratification can only be limited to rough differentiation of homework difficulty.

2.3 Experimental Validation and Evaluation Memorization

The experiment mainly focuses on confirmatory tasks such as K-nearest neighbor classification, where students reproduce the code, adjust parameters, and observe the results. The activity scope is limited to a single knowledge point. The course lacks comprehensive tasks that connect multiple modules of "data processing model training result evaluation", and students are unable to experience the interface relationships between modules in experiments. The evaluation is mainly based on the final exam paper, with a focus on concept definition and formula derivation. It measures memory

and recalculation, rather than systematic thinking and engineering ability. The bigger flaw lies in the lack of process data: teachers only receive a total score at the end of the semester, which cannot identify each student's weak knowledge points, and intervention can only be done in a "holistic tutoring" manner with equal effort. These two issues point to the same gap: the curriculum lacks a structure that can record learning trajectories, with trajectory granularity down to knowledge points.

3. Construction of Course Knowledge Graph

3.1 Definition of Four Level Structure and Relationships

The graph is organized into four levels: "course knowledge unit knowledge domain knowledge point". Knowledge units correspond to course modules, knowledge domains correspond to topics within modules, and knowledge points are the smallest units of teaching and assessment. Knowledge points are classified into five categories based on their teaching functions: conceptual, principled, methodological, case-based, and ethical. The edges between nodes are classified into five categories based on semantics, and their teaching functions are shown in Table 1.

Table 1. Types of Knowledge Point Relationships and Teaching Functions

Relationship type	Meaning	Teaching function
predecessor	Mastering A is a prerequisite for learning B	Generate learning paths, locate missing starting points
successor	B is an extension or advancement of A	Support layered expansion
contain	The knowledge domain includes knowledge points	Support knowledge framework navigation
intersection	A and B share the same principle or method	Support cross module integration
application	The principle applies to specific scenarios	Supporting Case Teaching

The type of knowledge point determines the form of linked resources, and the corresponding relationship between each knowledge unit, typical knowledge point, and linked resources is shown in Table 2.

Table 2. Knowledge Units, Typical Knowledge Points and Linked Resources

Knowledge Unit	Typical knowledge points	Type	Attach resources
Basic Concepts	Intelligent agents, Turing test	Conceptual	Courseware and micro lessons
Search and Reasoning	A * algorithm, α - β pruning	Methodological approach	Courseware and code
Machine Learning	K-nearest neighbor, decision tree, clustering	Methodological approach	Code, dataset
Deep Learning	Backpropagation, Convolutional Neural Networks	Principle based	Deductive lecture notes, code
Generative AI	Pre training fine-tuning paradigm	Conceptual	Micro lessons and case studies
Application and Ethics	Facial recognition, data privacy	Ethical considerations	Policy texts and discussion topics

3.2 Construction Process

The construction is divided into five steps: (1) breaking down knowledge units and domains based on the training plan and teaching syllabus. (2) Extract knowledge points from lecture notes, textbooks, and lab guides and label their types. (3) Annotate edges based on logical dependencies and methodological sharing relationships. (4) Attach courseware, micro lessons, code, and datasets to corresponding nodes. (5) Import the graph database for storage and visualize it on the teaching platform.

4. Teaching Implementation Based on Knowledge Graph

4.1 Overall Framework

The functions of graphs in teaching are threefold: content organization-storing and presenting knowledge according to graphs. Path navigation - generate learning paths along the edges. Data collection-recording learning behavior by node. The teaching process revolves around these three functions to form a feedback loop, as shown in Figure 1: the training objectives are decomposed into graph nodes, teaching is carried out along the graph, behavioral data flows back according to nodes, and evaluation diagnosis is used to revise the graph and teaching plan in reverse. The semantics of edges are the basis for path

generation and weak point diagnosis [9-11]: predecessor edges provide the order of filling gaps, intersecting edges provide migration clues, and cumulative data on nodes provide the mastery distribution of classes and individuals.

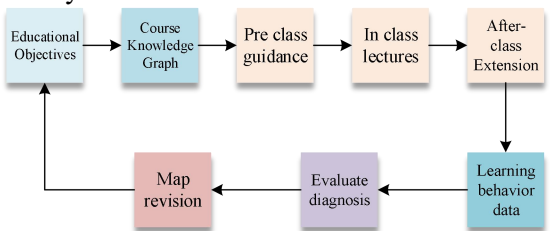


Figure 1. Schematic Diagram of Teaching Feedback Loop

4.2 Pre Class Guidance

Teachers post guidance task sheets on the platform, accompanied by visual learning maps. Students first browse the knowledge nodes and their precursor relationships of this content along the graph, establish connections between new and old knowledge, and then complete micro lesson learning and preview testing. The platform aggregates the answer results by knowledge points and generates a class mastery distribution map. The function of this stage is to replace the basis for teaching decisions from empirical estimation to measurement data: teachers determine the allocation of time during class based on node error rates, and prioritize the processing of nodes with high common error rates during class; The preview data also forms the individual baseline for post class streaming.

4.3 In Class Lectures

In class, the four steps of "case introduction - problem exposure - principle deduction - code verification" are followed, as shown in Figure 2, and the teaching sequence follows the precursor chain of the graph. Taking the deep learning unit as an example, the task is handwritten digit recognition, and the knowledge chain is perceptron → loss function → gradient descent → backpropagation → convolutional neural network: first, let students use perceptron to complete recognition and observe the failure boundary of the linear model, exposing cognitive gaps; Introduce loss function and gradient descent again to derive backpropagation; Finally, the task is completed using convolutional neural networks. After each theoretical node is explained, the corresponding code runs, and the formulas correspond one-to-one with the executable objects. The results of in class testing are written back to the graph nodes in real time, high-frequency error points are supplemented in class, and non compliant nodes are transferred to the post class path.

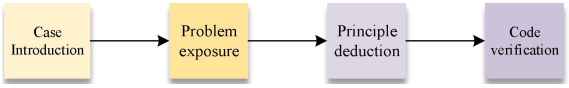


Figure 2. Schematic Diagram of the Four Step Process Taught in Class

4.4 After Class Expansion

Table 3. Three Stage Teaching Process

Stage	Teacher behavior	Student behavior	Graph function
Pre class	Publish a task list for guided learning. View and master the hot zone. Adjust the allocation of class hours	Browse the learning map. Complete micro lesson and preview testing	Present structure. Aggregate diagnostic data
In class	Teaching along the four steps of the precursor chain. In class testing. Instant supplementary lecture	Task driven learning. Code validation. Self testing in class	Provide a knowledge chain. Receive real-time feedback
After class	Publish hierarchical tasks. View node mastery	Fill in gaps or expand. Complete retest	Generate individual paths. Record behavioral data

Based on the results of comprehensive preview testing, in class testing, and chapter evaluation on the platform, students are divided according to their mastery of the nodes, as shown in Figure 3: those who fail to meet the standards are rolled back along the leading edge, supplemented with micro lessons, exercises, and code examples of weak nodes, and returned to the original node for retesting after completion; Qualified individuals enter comprehensive experimental projects or subject competitions for training, with task designs spanning multiple knowledge domains and mandatory use of intersecting edges in the graph. The behavioral data of both paths flow back to the graph, updating the node's grasp status and forming the input for the next round of pre class diagnosis. The summary of the three-stage teaching process is shown in Table 3.

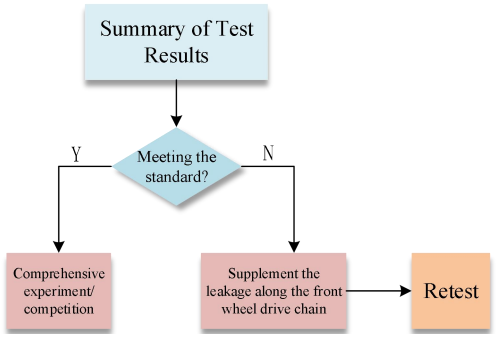


Figure 3. Schematic Diagram of Post Class Learning Path Diversion

5. Process Evaluation System

The evaluation consists of three main subjects: teacher evaluation, student self-evaluation, and group peer evaluation, covering four dimensions: knowledge mastery, practical ability, learning process, and comprehensive literacy. The indicators and data sources are shown in Table 4. The difference from the traditional "regular grades+final exam papers" lies in two points: first, granularity, where the graph places regular data into knowledge nodes rather than general attendance and homework impression scores; The second is continuity, where the mastery of nodes is updated sequentially with preview, in class, and chapter evaluation, forming a time series. Teachers can use this to determine whether students have "not learned" or "learned but not mastered". The weight allocation is determined by the course team based on the course objectives and filled in Table 4. There is no preset value here.

Table 4. Process Evaluation Index System

Evaluation dimension	Indicator	Data source	Evaluation subject	Weight
Knowledge mastery	Node mastery and accuracy of chapter evaluation	Graph node data, quizzes	System+Teacher	30%
Practical ability	Code completion and experimental report quality	Experimental platform, homework	Teacher	30%
Learning process	Pre study completion rate and performance of in class testing	Platform logs and classroom records	Teacher	20%
Comprehensive Literacy	Collaborative contribution, program integration, and defense performance	Mutual evaluation form, project defense	Group+Teacher	20%

6. Practical Effects and Improvements

The reform will be implemented in the School of Information Engineering at Nanjing Xiaozhuang University from the second semester of 2025-2026, with a total of 196 students studying Introduction to Artificial Intelligence, covering multiple majors. Teaching relies on online course platforms and graph databases to complete graph display, detection aggregation, and behavior recording.

The effects are compared item by item according to the three questions in Section 1, and the problems, measures, and observation indicators are shown in Table 5. This article does not report figures that have not been statistically tested. The indicator values are filled in by the course team after summarizing platform data and test scores.

There are three points to observe at the classroom level. Firstly, after teaching along the precursor chain, students began to use the chain of "loss function gradient backpropagation" in their experimental reports to explain debugging behavior, rather than copying definitions, indicating that knowledge is called in a structured rather than isolated manner. Secondly, the pre class hot zone diagnosis changes the allocation of classroom time from planned average to biased according to error rate. Common error nodes are repeated in class, and individual errors are taken the post class path, avoiding the "already learned students accompanying" caused by uniform repetition. Thirdly, the intervention of teachers on weak students has been changed from general guidance to filling gaps by nodes. Students can identify their specific weak points on the map, and the guidance corresponds one-to-one with the actual gaps of individuals. It should be noted that the above are classroom observations and platform process records, which are procedural evidence; the omparison conclusion at the score level will be provided separately after the completion of data statistics and testing.

This plan has three limitations. Firstly, implementing a single course for only one semester without parallel control classes cannot rule out interference factors such as increased teacher input and student novelty; Secondly, graph construction relies on manual

disassembly, resulting in high construction and revision costs; Thirdly, generative models have a fast iteration speed, and there is a risk of expiration for graph nodes and edges, which must be revised on schedule. Three follow-up tasks: accumulate multiple rounds of data for statistical testing; Set up a control group to separate interfering variables; Explore the use of large models to assist in knowledge point extraction and question generation, reduce graph maintenance costs, and integrate automatic question answering.

Table 5. Issues - Measures - Comparison of Observation Indicators

Original question	Reform measures	Observation indicators	Result
Knowledge associations are fragmented	Graph navigation+teaching by precursor chain	Average score of chapter evaluation. Knowledge Structure Questionnaire Score	Chapter evaluation average score 78.5 → 82.3. The score of the knowledge structure questionnaire ranges from 4.2 to 6.9
Conflict between unified progress and differences	Pre class hot zone diagnosis+post class dual pathway	Completion rate of filling gaps and pass rate of retesting. Expansion completion rate	The completion rate of missing paths is 87%.The retest pass rate is 76%; Expansion task completion rate of 91%
Experimental verification and evaluation memorization	Integration task+node level process evaluation	Comprehensive experiment completion quality. Process performance discrimination	The average score for comprehensive experiments is 81.6, with an excellent rate (≥ 90 points) of 23%

7. Conclusion

This article unifies the functions of content organization, path navigation, and learning behavior collection through a course knowledge graph. It provides a method for constructing the graph and a teaching process from pre class to in class to post class, and reconstructs a process evaluation based on node mastery. The implementation of the map in one semester, involving 196 people, shows that teaching, practice, and diagnosis share the same knowledge structure, and the granularity of weak point localization is refined from "class" to "knowledge points". The conclusion is limited by three factors: single round practice, no control group, and quantitative data to be statistically analyzed. Its generalizability needs to be tested through multiple courses and multiple rounds of controlled experiments.

Acknowledgments

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References

[1] Zhao Yingying, Zhu Shuaishuai. Research Review of Knowledge Graph Construction Technology, Computer Engineering, 2026, 52(8):84-100. (in Chinese)

[2] Yang Guanci, Xu Biao, Luo Kexin, et.al. Overview of Knowledge Graph Technology: Construction, Reasoning, and Typical Applications, Journal of Guizhou University (Nature Science), 2025, 42(2):1-10. (in Chinese)

[3] Sun Lijun, Meng Fanjun, Xu Xingjian. Survey of Research on Curriculum Know1edge Graph Coustructiou Techuiques, Computer Engineering, 2025, 51(11):1-21. (in Chinese)

[4] Li Yuzhuo. Reform and Exploration of Computer Network Course Teaching Based on Knowledge Graph. China E-commerce, 2026, 32 (17): 22-24. (in Chinese)

[5] Chen Xiaoling, Liu Fangmei, Ni Hao, et.al. Exploring Teaching Model of “PLC Principles and Applications” Course Based on AI Knowledge Graphs. Industrial Control Computer, 2026, 39(8): 164-166. (in Chinese)

[6] Zhang Siyan, Huo Da, Shao Xuan, et al. Construction of Knowledge Graph for the Course of Power Electronics Technology for Smart Education. China Modern Educational Equipment, 2026(15): 52-54. (in Chinese)

[7] Li Qinying, Wang Chuhan. Research on Adaptive Learning Dynamic Path Generation Method Based on Multimodal Knowledge Graph. Software Guide, 1-8.

https://link.cnki.net/urlid/42.1671.TP.20260409.1108.004. (in Chinese)

[8] Liu Qiao, Li Yang, Duan Hong, et. Al. Knowledge Graph Construction Techniques. Journal of Computer Research and Development, 2016, 53(3): 582-600. (in Chinese)

[9] Wang Haofen, Qi Guilin, Chen Huajun Knowledge Graph: Methods, Practices, and Applications. Beijing: Electronic Industry Press, 2019

[10] Xiao Yanghua Knowledge Graph: Concepts and Technologies. Beijing: Electronic Industry Press, 2020

[11] Xu Zenglin, Sheng Yongpan, He Li-rong, et. al. Review on Knowledge Graph Techniques. Journal of University of Electronic Science and Technology of China, 2016, 45(4): 589-606. (in Chinese).