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Dynamic Update Mechanism of the Knowledge Graph for AI Literacy Course

Yi Zeng [1, 2, 3], Lingling Shen [1, 2, 3, *], Yi Yin [1, 2, 3], Qian Gao [1, 2, 3], Chen Li [1, 2, 3], Yinan Tang [1, 3, 4], Yuanxi Zhang [1, 3, 4]

[1] School of Artificial Intelligence, Nanjing Normal University 210023, Nanjing, China

[2] School of Computer and Electronic Information, Nanjing Normal University 210023, Nanjing, China

[3] Artificial Intelligence Research Institute, Nanjing Normal University 210023, Nanjing, China

[4] Honors College, Nanjing Normal University 210023, Nanjing, China

[*] **Corresponding author**: (Email: llshen509@163.com)

Abstract: The rapid evolution of artificial intelligence has far outpaced the traditional 3–5-year revision cycles of university curricula, resulting in outdated instructional materials and limiting students' ability to understand emerging technologies. To address this challenge, this paper proposes a dynamic update mechanism for AI literacy course resources based on a knowledge graph. The mechanism integrates three core components: a technology-driven agile response system, an industry–academia collaborative injection mechanism, and a data-driven feedback and optimization loop. The agile response system employs frontier-technology tracking and multi-level content alerts to identify outdated knowledge in real time. The collaborative injection mechanism incorporates up-to-date industrial cases, datasets, and application scenarios, ensuring the practical relevance of teaching materials. The data-driven optimization mechanism leverages learning analytics to prioritize revisions, detect anomalies, and support rapid, atomic-level updates. By establishing an institutionalized workflow covering knowledge tracking, priority setting, content co-creation, review, publication, and effectiveness evaluation, the proposed framework transforms teaching resources from static repositories into dynamic knowledge services. This approach significantly enhances the timeliness, accuracy, and utilization efficiency of instructional materials while strengthening industry–education integration and improving students' engineering competencies. The dynamic update mechanism provides a sustainable pathway for AI literacy education to adapt to fast-changing technological landscapes and to cultivate future-ready talent.

Keywords: Artificial Intelligence Literacy, Knowledge Graph, Dynamic Update Mechanism, Frontier Technology Tracking, Data-Driven Optimization, Industry–Academia Collaboration, Educational Resource Management.

1. Introduction

The pace of innovation in artificial intelligence has far exceeded the traditional revision cycles of university curricula. Textbooks are typically updated every 3–5 years, whereas the "validity period" of frontier AI knowledge often lasts less than one year. As a result, course content frequently fails to capture ongoing transformations in the industry. Critical advances in technologies such as large-scale models and AIGC cannot be incorporated into teaching in a timely manner, preventing students from developing a comprehensive and forward-looking understanding of emerging technologies. Although conventional curriculum design emphasizes systematicity and stability, this structure increasingly reveals its obsolescence under rapid AI iteration.

Meanwhile, intelligent search engines and large-model-based question-answering tools are reshaping students' learning habits, reducing their reliance on unidirectional lecturing and imposing higher demands on instructors' capacity for continuous knowledge renewal. Consequently, pedagogical reform must shift from *static content transmission* toward *dynamic capability development*, placing greater emphasis on nurturing students' problem awareness, critical thinking, creativity, and human–AI collaboration skills. Only through such a transition can AI literacy courses maintain their vitality and leadership amid a rapidly evolving technological landscape.

2. Current Research

In the construction of knowledge graphs for AI literacy courses, existing studies have largely concentrated on structural modeling, standards development, and technical platforms [1]. Ying Li et al. [2] introduced the concept of Course-KG, along with its construction workflow and application scenarios, providing a theoretical foundation for knowledge-graph development in AI literacy education. Daniel Reales et al. [3] demonstrated how LLMs combined with knowledge graphs can be used to automatically identify core concepts, offering a promising approach for future graph expansion. Yajuan Bai et al. [4] illustrated the feasibility of applying knowledge graphs to interactive learning platforms, intelligent recommendation systems, and educational resource retrieval. Chunhong Liu et al. [5] further showed how knowledge graphs can be employed to design learning-path recommendation systems.

However, the update mechanisms adopted in these studies tend to be relatively rigid, making it difficult for the knowledge graphs to reflect cutting-edge technological developments in a timely manner. Existing evaluation frameworks emphasize quantitative indicators while lacking continuous optimization and dynamic maintenance of knowledge nodes. Moreover, dissemination is often implemented in a top-down manner, with insufficient participation from instructors and industry practitioners, which hinders deep integration into classroom teaching. At the same time, limited interoperability among educational platforms has led to fragmented knowledge and pronounced "information-island" effects, thereby constraining the practical value of such systems in supporting pedagogical reform.

3. Overall Technical Architecture

3.1. Technology-Driven Agile Response Mechanism

Establishing a technology-driven agile response mechanism constitutes a core step toward addressing the timeliness challenges of instructional resources. The central idea is to develop a frontier-technology tracking system and integrate it seamlessly with a content-alert module within the knowledge graph, thereby enabling rapid identification, classification, and updating of relevant knowledge units.

(1) Construction of an AI Frontier-Technology Tracking System

This system is designed to continuously monitor, collect, and analyze the latest developments within the AI ecosystem through automated tools, providing up-to-date inputs to the knowledge repository. Distributed crawlers and official APIs from target sources—such as open-source communities, academic platforms, industry news outlets, and developer Q&A forums—can be employed for high-frequency, targeted data acquisition. Newly detected knowledge items are then processed using natural language processing techniques and matched against the existing knowledge-graph database, through which they can be rapidly identified as additions, modifications, or replacements of current nodes.

(2) Designing a Multi-Level AI Content Alert System

Once frontier AI knowledge is identified by the tracking system, an alert mechanism must be activated to trigger the dynamic update workflow of the knowledge graph. The timeliness of each knowledge node can be assessed by computing the semantic similarity or version-difference score between existing instructional resources and the most recent external knowledge. Based on the resulting obsolescence-risk value, alerts may be classified into different levels, each of which automatically initiates a corresponding action.

High-risk items (Level-1 alerts) are flagged for mandatory updates; medium-risk items (Level-2 alerts) are labeled as recommended for revision; and low-risk items (Level-3 alerts) are assigned to periodic review cycles. Updated technical keywords and tags can be automatically appended to relevant resources. An automatically generated "content-update discrepancy report" highlights conflicts or omissions between current materials and newly identified external knowledge, thereby supporting targeted revisions by system maintainers.

Through this agile response mechanism, the AI knowledge repository is transformed from passively receiving feedback to proactively detecting and reacting to technological change, substantially enhancing the timeliness of instructional resources.

3.2. Industry–Academia Collaborative Injection Mechanism

Industry–academia collaboration constitutes a crucial mechanism for ensuring both the practical relevance and the timeliness of instructional resources. It enables the continuous infusion of the latest technological applications, real-world cases, and developmental trends from the AI industry into the knowledge repository, thereby effectively bridging the temporal gap between university research and industrial demand.

To begin with, the establishment of an institutionalized and regularized framework for university–enterprise cooperation forms the foundation of this injection mechanism. Such a framework allows cutting-edge hardware, software platforms, industry datasets, and project environments from AI companies to be introduced into the academic setting, serving as a "live source" for student practice and instructional content development.

In addition, well-defined procedures and standards should be formulated to regulate enterprise participation in co-construction, content review, and case contribution. Through this structured collaboration, the knowledge graph for AI literacy education can receive a continuous flow of industry-aligned, up-to-date information—effectively providing "fresh blood" that enables sustained and dynamic updating of teaching resources.

3.3. Data-Driven Feedback and Optimization Mechanism

A data-driven feedback and optimization mechanism functions as the internal cycle that enables continuous updates to the AI literacy course knowledge base. By collecting and analyzing user-interaction data within the resource pool, this mechanism replaces traditional low-efficiency feedback channels and supports precise optimization of teaching materials as well as priority ranking for updates.

(1) Design of Learning-Data Collection and Analysis Models

A learning-data analytics model should be established to quantify the actual pedagogical effectiveness of resources and users' satisfaction levels. This can be achieved through the integrated analysis of three categories of data: popularity, learning behaviors, and error-related signals. Metrics such as page views, download counts, and the proportion of new visitors can be used to assess the attractiveness and timeliness of learning resources. Average viewing time, completion rates, and bounce rates help evaluate instructional effectiveness. Meanwhile, error reports, execution logs, and negative feedback serve as indicators for monitoring the accuracy and reliability of the materials.

(2) Precision Optimization and Priority Ranking Mechanism

When a learning resource exhibits a high obsolescence risk while still maintaining high popularity, it indicates that the material represents a critical instructional concept whose content is no longer aligned with current technological developments. Such resources should therefore be prioritized for urgent revision. If a resource is not outdated but shows a high bounce rate or low completion rate, this suggests deficiencies in structural design, presentation format, or learning-path configuration; these materials should be improved through restructuring, enhanced interactivity, or optimized presentation. Conversely, resources that show persistently low popularity and minimal usage can be regarded as having limited instructional value or having been effectively replaced by superior content; such items should be flagged for elimination or integration with other resources. Through this data-driven priority-ranking mechanism, optimization efforts can be more focused and more efficient in supporting pedagogical reform.

(3) Real-Time Feedback and Correction Loop

The results of data analysis directly trigger a rapid, atomic-level correction workflow, addressing the long-standing problems of slow and delayed feedback in traditional resource-updating processes. When anomalies are detected through learning analytics, the intelligent layer immediately identifies all related atomic resources and generates an update-discrepancy report, after which maintainers are prompted to apply corrections. For minor issues, an atomic-editing interface allows updates to be completed swiftly. Once revisions are finalized, the new version automatically replaces the old one and update notifications are pushed in real time to all relevant courses, ensuring that the resource ecosystem remains continuously up-to-date. Through this mechanism, the teaching-resource pool evolves from a static repository into a dynamic knowledge-service system capable of self-diagnosis and real-time iteration. This transformation supports long-term sustainability and adaptive evolution, greatly enhancing the efficiency and quality of educational reform.

4. Pathways for Implementing the Dynamic Update Mechanism

4.1. Dynamic Update Mechanism

The implementation workflow integrates the core components—the agile response mechanism, the industry–academia collaboration mechanism, and the data-driven optimization mechanism—into a closed-loop process for continuous updating. As shown in Table 1, the implementation of the dynamic update mechanism for the AI literacy course knowledge graph consists of five stages: knowledge tracking and alerting, priority ranking and project initiation, co-construction and revision, review and publication, and effectiveness evaluation and feedback.

Table 1. Implementation Workflow of the Dynamic Update Mechanism for the AI Literacy Course Knowledge Graph

Phase	Core Task	Technology-Driven Mechanism
I. Knowledge Tracking & Early Warning	Monitor emerging technologies in real-time; identify knowledge changes and outdated resources.	Technology frontier tracking system; timeliness evaluation engine
II. Priority Setting & Project Initiation	Determine urgency of resource updates or retirements based on warnings and user feedback.	Learning data analysis models; priority ranking algorithms
III. Content Co-creation & Revision	Quickly revise or deeply restructure content; integrate latest industry cases.	Collaboration & version control services; rapid feedback and revision interfaces
IV. Review & Release	Conduct dual review for academic and industry accuracy; release updated versions promptly.	Atomic release service; dual-review mechanism
V. Effect Evaluation & Feedback	Continuously monitor resource usage and user satisfaction; feed data back to Phase I.	User and behavior log database; popularity analysis models

4.2. Safeguard Measures

To ensure the long-term effectiveness of the dynamic mechanism, updates should be institutionalized. A resource validity and retirement threshold system should be established, whereby content repeatedly flagged by the timeliness model and not updated in time is automatically removed or archived, addressing dormant resources. Simultaneously, standardized industry–education collaboration should be promoted, integrating enterprise experts' case contributions, content review, and part-time guidance into the school management system with stable funding and cooperation mechanisms. Additionally, clear resource ownership and usage policies should be established through Creative Commons licenses or internal permissions, defining the rights, responsibilities, and benefits of teachers, schools, and enterprises, thereby facilitating open sharing and collaborative development.

4.3. Application

(1) Enhance Timeliness and Accuracy of Teaching Resources

By leveraging frontier technology tracking and timeliness evaluation models, resource updates shift from "slow iteration" to "continuous refresh," ensuring course content keeps pace with industry developments. Resource validity and retirement mechanisms promptly remove outdated content, preventing the accumulation of obsolete materials. Data-driven automatic alerts and rapid revision processes further improve resource quality, keeping the curriculum accurate, reliable, and continuously active.

(2) Promote Deep Industry–Academia–Research Integration and Enhance Practical Teaching

Through institutionalized industry–education collaboration, enterprise cases and industry data are continuously incorporated into courses, forming a stable, bidirectional update loop. Real engineering scenarios and the latest technological outcomes enrich classroom teaching, significantly enhancing its practicality and relevance. This mechanism fosters co-construction and sharing between schools and enterprises, strengthening students' mastery of cutting-edge technologies, improving engineering skills and employability, and supporting the goal of cultivating outstanding talents.

(3) Improve Resource Utilization Efficiency and User Experience

Knowledge-graph–based intelligent recommendation can accurately match teachers' needs, improving lesson preparation and resource retrieval efficiency. Learners can access high-quality content more quickly through personalized recommendations. Version control and collaborative mechanisms encourage teachers, experts, and students to participate in resource development, fostering a culture of continuous co-creation and transforming the resource repository from static storage into an efficient, collaborative, and dynamic knowledge ecosystem.

5. Conclusion

The core challenges of rigid mechanisms and poor timeliness in teaching resources for general artificial intelligence courses are addressed in this paper. A dynamic update mechanism for AI curriculum resources, based on a knowledge graph, is proposed. This mechanism transforms resource management from static storage to dynamic knowledge services, effectively ensuring the courses remain cutting-edge, practical, and accurate. It will help the education system better adapt to the challenges of the AI era and cultivate high-quality, future-ready talents.

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