Practical Research on Knowledge Graph-Driven Intelligent Teaching Models: A Case Study of Local Applied Universities

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Abstract. Local applied universities face a critical challenge: traditional teaching often delivers fragmented knowledge, failing to cultivate the systematic competencies required by industry. To address this, we propose and implement an intelligent teaching model centered on a domain-specific knowledge graph (KG). Our model integrates three layers—systematized knowledge, tiered competencies, and scenario-based literacy—into a dynamic closed-loop system that personalizes learning and provides actionable feedback. We constructed a KG for a Probability Theory course using entity-relationship-attribute triples extracted from multi-source data. An empirical study at Ordos Institute compared two cohorts taught by the same instructor with identical materials; one used our KG-driven model, the other traditional methods. Results showed the experimental group significantly outperformed the control group in final exam scores (68.7 vs. 61.8, p=0.007), with a notable 11.25-point advantage at the 25th percentile. This paper offers a practical, evidence-based blueprint for leveraging KG technology to bridge the gap between academic instruction and real-world application in resource-constrained settings.

Keywords: Knowledge Graph, Intelligent Teaching, Teaching Reform, Local Applied Universities

1 Introduction

Higher education, particularly at local applied universities, is often criticized for its "fragmented knowledge delivery" and inability to foster the integrated, problem-solving competencies demanded by modern industries. Students graduate with isolated facts but lack the ability to synthesize knowledge into actionable solutions. While national strategies like "Education Informatization 2.0"[1] call for digital transformation, a practical, scalable model for achieving this in resource-limited institutions remains elusive.

Existing research on intelligent education has explored knowledge graphs (KGs) in fields like medicine and engineering, demonstrating their power to structure information[2-5]. However, these studies often focus on elite institutions or specific technical domains, leaving a significant gap for applied universities that serve a broad student

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population with diverse needs. This paper directly addresses this gap by presenting a practical, KG-driven intelligent teaching model designed explicitly for the context of local applied higher education. Our work contributes a replicable framework that moves beyond theoretical discourse to demonstrate tangible learning improvements.

2 Theoretical Framework Construction

Our model is built upon the foundational premise that effective teaching must connect structured knowledge with authentic application[6-7]. We define a knowledge graph as a semantic network that formalizes a domain's concepts (entities), their interrelations (relationships), and properties (attributes) into machine-readable triples. Intelligent teaching, in our context, leverages such a graph to create a responsive, data-driven learning environment that adapts to individual learner pathways.

The core of our framework is a three-layer architecture (Figure 1):

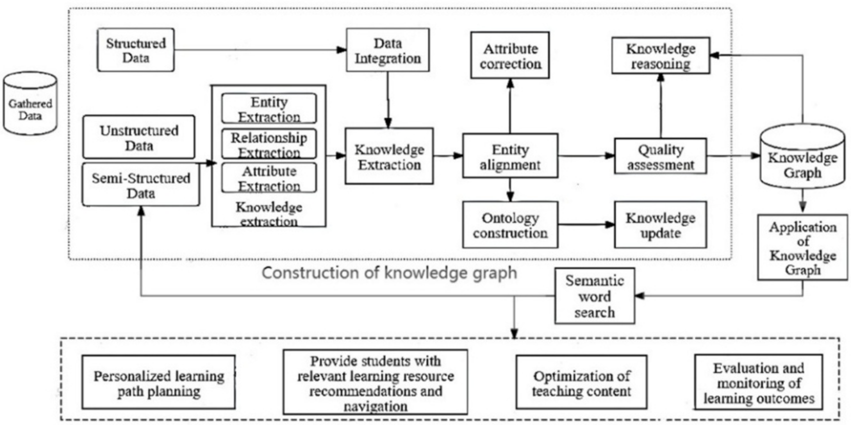

Fig. 1. Knowledge Graph-Driven Intelligent Teaching Model

First, knowledge graph technology is employed to construct a course knowledge graph. Based on data collection and existing teaching resources, the gathered data is categorized into structured, unstructured, and semi-structured data [8-9]. Structured data refers to "formatted tables," unstructured data encompasses "free text, images, audio, and video," while semi-structured data denotes "flexible formats with labels but without strict constraints" [10-11]. For structured data, after integration, knowledge extraction is performed, followed by establishing relationships between knowledge entities to construct "entity-relationship-attribute" triples[12-13]. For unstructured data, entity, relationship, and attribute extraction must first occur to achieve knowledge extraction; subsequent steps mirror those for structured data [14-15]. Continuous knowledge updates and information corrections then complete the knowledge graph construction.

The knowledge graph layer serves as the core schema support layer, undertaking the central functions of knowledge representation and resource association. This layer uses a knowledge graph tailored to the curriculum systems of local applied universities as its core carrier. It precisely displays core course knowledge points, competency requirements, teaching objectives, hierarchical relationships (e.g., prerequisite-advanced) and cross-associations (e.g., cross-chapter application links) between knowledge points. It also integrates industry practice cases and knowledge application scenarios. Concurrently, it precisely maps resources—including instructional videos, textbook content, question banks, and practical projects—to specific knowledge points within the graph. This achieves structured organization and semantic linkage of resources, providing data and knowledge foundations for subsequent applications. The constructed knowledge graph enables both hierarchical exploration through layered clicks and direct search-based navigation. The knowledge graph-driven smart education model applies the constructed knowledge graph to optimize teaching content, assess learning outcomes, and support personalized learning paths.

The Teaching Application Layer serves as the implementation layer for model deployment, focusing on the intelligent organization of teaching resources and the precise execution of teaching processes. Leveraging the resource association network from the knowledge graph layer and integrating student learning behavior data (such as knowledge gaps and learning progress), it enables personalized teaching resource recommendations (e.g., delivering explanatory videos and supplementary exercises for weak knowledge points) alongside dynamic resource updates and optimization. The Personalized Learning Services module analyzes student learning paths and knowledge mastery states through knowledge graphs, enabling students with varying foundations and learning needs to independently access related resources for specific knowledge points. The Precision Teaching Implementation module provides instructional decision support for teachers. By visualizing the class's overall knowledge distribution via knowledge graphs, it assists educators in pinpointing key teaching challenges, dynamically adjusting pacing, and refining instructional strategies.

The Assessment Feedback Layer serves as the optimization assurance layer, enabling personalized learning outcome evaluations and iterative refinement of the teaching system. Quantitative assessment evaluates students based on learning behavior data linked to the knowledge graph—such as preview completion rates, classroom interaction frequency, and test accuracy—alongside midterm and final assessment data. Data analysis reveals the depth of students' knowledge mastery while collecting specific issues encountered by teachers during instruction. Assessment results are fed back into the knowledge graph layer and teaching application layer. This process supplements knowledge graph gaps and missing practical scenarios, drives model optimization, and ensures continuous refinement of the system.

This model encompasses the knowledge graph layer, teaching application layer, and assessment feedback layer, forming a deeply interactive relationship through a dynamic closed-loop system. The knowledge graph layer provides the foundational knowledge and resources for the instructional application layer. Implementation data from the instructional application layer flows in real-time to the assessment feedback layer. Outcomes from the assessment feedback layer then drive the optimization of the knowledge graph layer and adjustments to the instructional application layer, enabling continuous iteration of the model. This model achieves three core objectives: First, intelligent organization of instructional resources, breaking away from the fragmented storage of traditional resources. Through semantic associations within the knowledge graph, resources are structurally integrated and personalized for adaptation. Second, it enables precise implementation of teaching processes. Leveraging the knowledge graph's accurate profiling of student learning states, it facilitates the execution of personalized teaching strategies. Third, it delivers personalized assessment of learning outcomes. Moving beyond traditional single-metric grading, it employs comprehensive data collection throughout the learning journey and multi-dimensional evaluation metrics based on the knowledge graph. This enables holistic assessment of students' knowledge mastery, skill development, and learning experience.

3 Knowledge Graph Construction and Practical Design

We implemented our model in a core "Probability Theory and Mathematical Statistics" course. The KG was constructed by applying data mining and natural language processing (NLP) techniques to extract "entity-relationship-attribute" triples from multi-source educational materials, including textbooks, lecture PPTs, and historical question banks. This process transformed unstructured content into a structured, queryable knowledge base.

The practical teaching design leveraged this KG to create a personalized learning journey:

Pre-study: The system generated individualized learning paths based on a student's prior knowledge, highlighting prerequisite concepts from the KG.

Review: After class, the system recommended targeted review materials by identifying weak links in the student's personal knowledge sub-graph.

Q&A Support: A chatbot, powered by the KG, provided instant, contextual answers to student queries, linking explanations directly to relevant course concepts.

This design ensured that the abstract structure of the KG was translated into concrete, daily learning support for every student.

4 Evaluation and Analysis of Teaching Practice Outcomes

To validate our model, we conducted a quasi-experimental study at Ordos Institute during the 2022-2023 academic year. Two parallel classes for the same major were selected, both taught by the same instructor using identical textbooks and syllabi. The control group (n=43) followed traditional lecture-based instruction in the fall semester, while the experimental group (n=42) used our KG-driven intelligent teaching model in the spring semester.

Final exam scores served as the primary quantitative metric. A bar chart comparing the final exam scores of the two classes is shown in Figure 2. The chart reveals that starting from 70 points, the proportion of students in the experimental class is higher. Notably, while no student in the regular class scored above 90, the experimental class had 3-4 students achieving this score. In the mid-range score band of 60-69 points, the number of students in both classes is comparable. However, in the lower score bands—

specifically those below 60 points—the regular class consistently has a higher number of students.

Furthermore, making two sample t test of the two classes' final score. The results were statistically significant:

The experimental group achieved a higher mean score (68.7) compared to the control group (61.8).

The difference was even more pronounced among lower-performing students, with an 11.25-point gap at the 25th percentile.

An independent samples t-test confirmed the significance of this improvement (t = -2.738, p = 0.007).

This data demonstrates that the KG-driven model not only lifted overall performance but was particularly effective in supporting students who typically struggle, suggesting its potential to enhance educational equity.

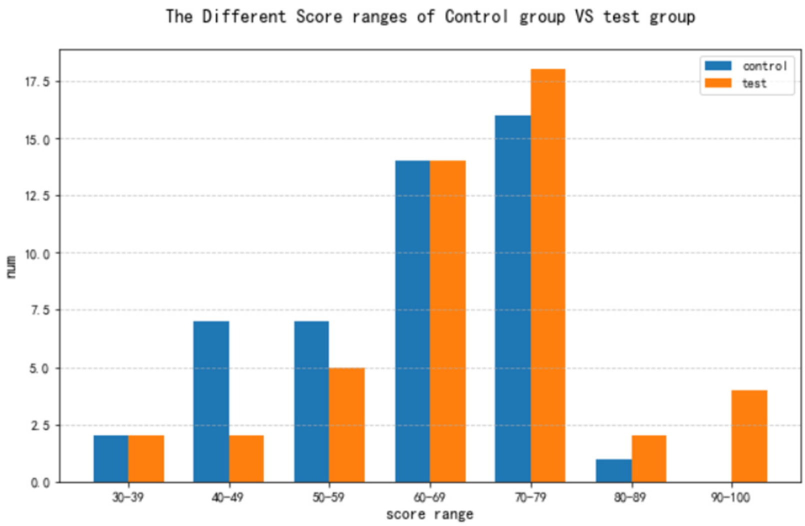

Fig. 2. The different score ranges of control group VS test group

5 Conclusion

This study successfully developed and validated a practical, knowledge graph-driven intelligent teaching model tailored for local applied universities. By integrating systematized knowledge, tiered competencies, and scenario-based literacy into a dynamic closed-loop system, our approach directly tackles the problem of fragmented learning. The empirical evidence from a real-world Probability Theory course confirms its effectiveness in improving student outcomes, especially for those at the lower end of the performance spectrum.

While our pilot focused on a single course, the framework is inherently scalable. Future work will explore embedding real-world enterprise projects into the KG to further strengthen the industry-academia link and expand the model to other foundational STEM courses. This research provides a crucial step toward a more intelligent, equitable, and effective future for applied higher education.

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