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AI-Enabled Teaching Reform of Database Principles and Technology

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Abstract: The rapid advancement of database technology has fundamentally reshaped skill requirements across industries such as finance, e-commerce, and intelligent manufacturing. However, traditional teaching approaches to database courses in business-oriented programs face persistent challenges, including the cognitive gap between abstract theoretical concepts and real-world business scenarios, limited laboratory exercises disconnected from industry demands, and inefficient conventional teaching evaluation mechanisms. This study proposes and implements a comprehensive AI-enabled teaching reform framework integrating three core modules: (1) an AI-driven knowledge graph system for theoretical teaching, which constructs a structured knowledge corpus by integrating domain textbooks, accounting practice documents, and big data industry case repositories, with 186 database concept nodes, 94 application scenario nodes, and 412 semantic relationship edges to visualize complex concept relationships; (2) a generative AI-powered virtual business scenario platform with an intelligent SQL assessment engine, featuring a multi-modal generative model trained on domain-specific knowledge bases to produce 12 distinct synthetic business datasets with complete business logic chains and statistical consistency, along with a dual-path detection mechanism combining static syntax tree analysis and dynamic execution result evaluation for SQL assessment; and (3) a multimodal data-driven teaching evaluation and feedback mechanism, establishing a data integration pipeline connecting virtual scenario platform logs, classroom response system interaction data, and online assessment results, employing ensemble learning algorithms and clustering analysis to construct student ability profiles and identify collective learning patterns.

Keywords: AI in Education; Knowledge Graph; Generative AI; Database Curriculum Reform; Intelligent Assessment; Data-driven Teaching Evaluation

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1 Introduction

The digital transformation of global industries has fundamentally reshaped the skill requirements for business professionals in the 21st century. Database technology, as the cornerstone of data management and analytics, has become indispensable across sectors including financial services, supply chain management, and digital marketing [1]. In response, universities have increasingly integrated database courses into business-oriented curricula, particularly within accounting, business administration, and information management programs. Despite the growing importance of database literacy, pedagogical practices in this domain continue to encounter persistent structural challenges that undermine teaching effectiveness and student learning outcomes.

Traditional teaching approaches to the "Database Principles and Technology" course are predominantly characterized by a lecture-based transmission model, where theoretical concepts such as relational algebra, normalization theory, and query optimization are delivered through static

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presentations. This pedagogical approach suffers from three critical deficiencies. First, the inherent abstraction of core database concepts creates significant cognitive barriers for students, particularly those from non-technical backgrounds, who struggle to establish meaningful connections between theoretical principles and practical business applications [2]. Second, laboratory exercises typically rely on standardized, pre-defined datasets which lack the complexity and diversity of real-world business scenarios, thereby limiting students' ability to transfer learned skills to authentic professional contexts [3]. Third, prevailing assessment methods—primarily final examinations and structured lab reports—provide only coarse-grained feedback on learning outcomes, failing to capture dynamic learning behaviors or to generate timely, targeted interventions [4].

In recent years, artificial intelligence technologies have emerged as promising tools to address these pedagogical challenges. Research has demonstrated the positive effects of AI-enabled educational tools on student learning outcomes across diverse disciplinary contexts [5, 6]. Knowledge graphs have been applied to visualize programming concept relationships and support adaptive learning pathways [7, 8]. Generative AI has shown effectiveness in producing contextually relevant practice problems, creating simulated professional scenarios, and providing personalized feedback [9–11]. Learning analytics has enabled fine-grained learner profiling and real-time diagnostic insights [12]. However, the holistic integration of these AI technologies within the specific context of database education for business-oriented majors—where students possess limited technical backgrounds yet require both conceptual understanding and practical skills—remains underexplored [13]. Recent systematic reviews have highlighted the gap in empirically validated AI integration frameworks for database instruction, particularly for non-computer science majors [14, 15].

This study seeks to address this research gap by designing and implementing an AI-enabled teaching reform framework for the "Database Principles and Technology" course. Specifically, it aims to: (1) design and implement an AI-driven knowledge graph system integrating domain textbooks, accounting practice documents, and big data industry case repositories; (2) develop a generative AI-powered virtual business scenario platform with an intelligent SQL assessment engine; (3) construct a multimodal data-driven teaching evaluation mechanism; and (4) evaluate the effectiveness of the proposed reform through quasi-experimental field trials. The findings contribute to the theoretical understanding of AI-enabled curriculum reform and provide a replicable and scalable model for database education enhancement.

2 Materials and Methods

2.1 Research Context

The study was conducted at Hangzhou Normal University's Alibaba Business School, which emphasizes the integration of business education with cutting-edge technology. The "Database Principles and Technology" course is a core required course for two undergraduate programs: Accounting (approximately 50 students per cohort) and Big Data Management and Application (approximately 50 students per cohort). Students in both programs typically enter university with limited prior exposure to programming or database systems.

2.2 Research Design

This study employs an action research design with quasi-experimental elements. Over four implementation phases spanning March 2025 to February 2027, the reform was iteratively developed, piloted, evaluated, and refined. Data collection followed a mixed-methods approach, integrating quantitative learning outcome data with qualitative feedback from students and instructors.

2.3 Module 1: AI-Driven Knowledge Graph for Theoretical Teaching

A comprehensive knowledge corpus was constructed by integrating three categories of source materials: (1) the primary textbook ("Database Principles and Applications," 4th edition), covering relational algebra, SQL, normalization, indexing, and query optimization; (2) accounting practice documents, including ERP system operation manuals, financial statement database design guidelines, and tax declaration database schemas; and (3) big data industry case repositories, including e-commerce user behavior database design manuals and logistics inventory management case studies.

NLP techniques were employed to extract core database concepts and their semantic relationships. The technical stack included spaCy for linguistic feature extraction, complemented by fine-tuned transformer models (BERT-based) for semantic role labeling and relation extraction. Each extracted concept was annotated with cross-disciplinary mapping tags linking technical database concepts to relevant accounting or big data analytics application scenarios. Recent advancements in LLM-powered knowledge graph construction were leveraged to improve the accuracy of relationship extraction from unstructured educational content [8, 16].

The structured knowledge graph was implemented using Neo4j. Nodes represented database concepts (e.g., "normalization," "BCNF," "index optimization"), application scenarios (e.g., "ERP supplier master data management"), and prerequisite relationships. Edges encoded multiple relationship types including "prerequisite_of," "application_in," "analogous_to," and "contrast_with." An interactive visualization interface featured a professional-domain view switcher, allowing students to explore the same knowledge graph from an accounting perspective or a big data analytics perspective. A GPT-3.5-based conversational agent was fine-tuned using LoRA techniques, integrated with the knowledge graph to enable contextually grounded responses, following recent best practices for intelligent tutoring systems [17, 18].

2.4 Module 2: Generative AI-Powered Virtual Scenario Platform for Practical Training

The data generation layer was built upon a multi-modal generative model trained on domain-specific knowledge bases, including accounting annual report templates, cross-border tax declaration rules, and e-commerce transaction log structures. The generative model produced synthetic datasets preserving complete business logic chains and statistical consistency with real-world industry data in terms of dimensional structure, value distributions, and referential integrity relationships, aligning with recent approaches for authentic learning scenario generation [19].

A demand-driven task generation engine was developed to decompose enterprise-level business requirements into progressive experimental objectives. Each task sequence followed a structured progression: data modeling (conceptual design → logical design → physical implementation) → query formulation (basic retrieval → complex joins → optimization) → performance analysis, consistent with recommended pedagogical sequences for SQL education [20, 21].

The intelligent assessment engine employed a dual-path detection mechanism combining static syntax tree analysis and dynamic execution result evaluation. The static analysis path parsed students' SQL syntax trees to identify structural issues. The dynamic evaluation path analyzed execution plans to detect time complexity deficiencies. An error pattern knowledge graph was constructed by aggregating two semesters of student submission data, mapping high-frequency error patterns to underlying conceptual knowledge gaps, building upon recent advancements in automated SQL feedback systems [22, 23].

2.5 Module 3: Multimodal Data-Driven Teaching Evaluation Mechanism

A multimodal data integration pipeline was established, connecting three primary data sources: (1) the virtual scenario platform's operational logs, capturing SQL submission sequences, error patterns, time-on-task distributions, and revision trajectories; (2) the classroom response system's interaction data; and (3) the online assessment system's test result data.

Two complementary modeling approaches were employed. First, ensemble learning algorithms (gradient boosting decision trees) were trained to construct student ability profiles along multiple knowledge dimensions. Second, clustering analysis (k-means with silhouette-based parameter tuning) was applied to identify collective learning patterns within each cohort. Association rule mining discovered correlations between students' experimental error patterns and their mastery levels of specific knowledge concepts.

An instructor-facing decision support dashboard was developed, displaying real-time visualizations including knowledge heatmaps, experiment error distribution radar charts, student ability clustering results, and predictive at-risk alerts.

2.6 Data Collection and Analysis

Quantitative data were collected through pre- and post-intervention conceptual knowledge assessments (40 items), SQL coding assessments evaluated across correctness, efficiency, and code quality dimensions, and end-of-course evaluations capturing self-reported learning engagement.

Qualitative data were collected through semi-structured interviews with 24 randomly selected students (12 from each program) at the conclusion of each pilot semester. Quantitative data were analyzed using paired-sample t-tests and ANCOVA; effect sizes were reported using Cohen's d. Qualitative data were analyzed using thematic analysis following Braun and Clarke's six-phase protocol [24].

3 Results

3.1 Implementation Progress

As of the current stage (approaching the conclusion of Phase 3), the implementation has proceeded as follows. Phase 1 (March–August 2025) completed comprehensive literature review, stakeholder needs analysis through semi-structured interviews with 60 students, and finalized the technical architecture. Phase 2 (September 2025–January 2026) completed the knowledge graph system, containing 186 database concept nodes, 94 application scenario nodes, and 412 semantic relationship edges; the generative AI data synthesis engine was trained and validated, producing 12 distinct synthetic business datasets. Phase 3 (February–July 2026) conducted pilot teaching in one Accounting class ($n = 47$) and one Big Data Management class ($n = 51$), covering the Spring 2026 semester.

3.2 Conceptual Knowledge Acquisition

Comparing pre- and post-intervention assessment scores, students in the pilot cohorts demonstrated a statistically significant improvement in conceptual knowledge acquisition. The mean score on the conceptual knowledge assessment increased from 62.4 (SD = 11.3) at pre-intervention to 78.6 (SD = 9.7) at post-intervention, representing an average improvement of 16.2 percentage points (paired $t = 11.34$, $p < 0.001$, Cohen's $d = 1.52$). The most substantial improvements were observed in the modules covering relational algebra (mean improvement: 19.8 points) and normalization theory (mean improvement: 18.4 points)—precisely the two modules where knowledge graph visualization was most intensively utilized. Compared with historical control cohorts from the previous academic year ($n = 94$, mean post-intervention score = 71.2, SD = 10.5), the pilot cohorts showed a significantly higher post-intervention score ($t = 5.67$, $p < 0.001$, Cohen's $d = 0.78$). These results align with recent findings on knowledge graph-enabled conceptual learning in technical disciplines [8, 17].

3.3 SQL Coding Proficiency

SQL coding proficiency was assessed through three laboratory assessments administered at Weeks 4, 8, and 12 of the semester. Performance was evaluated across three dimensions: correctness, efficiency, and code quality. Results demonstrated progressive improvement across all three dimensions over the semester. The mean correctness score increased from 68.3% at Week 4 to 86.7% at Week 12. The mean efficiency score rose from 54.2 to 75.8 over the same period. The mean code quality score improved from 49.6 to 72.4. These improvements were statistically significant across all dimensions (repeated measures ANOVA, $p < 0.001$ for all three).

The error pattern analysis revealed that the most common initial errors (Weeks 1–4) included cartesian products from missing join conditions (78% of students), inconsistent use of NULL handling (63%), and missing index utilization in large table queries (59%). By Week 12, the incidence of these errors had decreased to 18%, 24%, and 31% respectively. These error reduction rates are comparable to those reported in recent studies of AI-powered SQL tutoring systems [22, 23].

3.4 Student Learning Engagement

Mean weekly platform login frequency was 4.7 times per week (vs. 2.1 for historical controls). Mean time spent on laboratory tasks was 87 minutes per week (vs. 54 minutes for historical controls). Notably, 67% of pilot students voluntarily explored the knowledge graph system for at least one additional session per week beyond assigned readings. End-of-course survey results indicated that 82% of students reported increased motivation for database learning due to the AI-enhanced course design, consistent with prior findings on authentic scenario-based learning [19, 25].

3.5 Qualitative Findings

Thematic analysis of student interview transcripts revealed four primary themes. Theme 1: Enhanced Conceptual Understanding through Visual Mapping. Students consistently reported that the knowledge graph visualization significantly improved their ability to understand the relationships between abstract database concepts and concrete business applications. Theme 2: Increased Motivation through Realistic Scenarios. Students in both programs reported higher motivation when tasks were embedded in professionally relevant business contexts. Theme 3: Value of Personalized Feedback. The intelligent assessment engine's personalized feedback received overwhelmingly positive evaluations. Students specifically valued the system's ability to identify the root cause of their errors rather than merely marking answers as correct or incorrect. Theme 4: Desire for Greater Integration. Several students expressed the desire for deeper integration between the knowledge graph and the experiment platform.

4 Discussion

The findings of this study contribute to the theoretical understanding of AI-enabled curriculum reform in several important ways. First, the results provide empirical support for the application of Cognitive Load Theory [26] to the design of AI-enhanced educational tools. The substantial improvement in students' understanding of relational algebra and normalization theory—the two modules with the highest intrinsic cognitive load—suggests that knowledge graph visualization effectively reduces extraneous cognitive load by externalizing and contextualizing complex concept relationships. This aligns with recent research on synergies between knowledge graphs and large language models for reducing cognitive load in technical education [16, 18].

Second, this study extends situated learning theory [27, 28] by demonstrating that generative AI can be effectively used to create authentic professional scenarios at scale within traditional academic settings. The significant improvement in students' SQL coding proficiency and engagement, particularly within the context of industry-relevant business tasks, supports the hypothesis that AI-generated realistic scenarios can bridge the theory-practice divide that has long challenged technical education. These findings add to the growing body of evidence supporting the use of generative AI for authentic learning design in database education [14, 19].

Third, the multimodal data-driven evaluation mechanism contributes to the emerging literature on learning analytics in discipline-specific educational contexts [12]. The finding that error pattern knowledge graphs—mapping students' procedural errors to underlying conceptual knowledge gaps—significantly enhanced the diagnostic power of formative assessment suggests a promising direction for graph-based analytics in education. Recent studies have demonstrated similar benefits of knowledge graph-based error analysis in programming education [8, 17].

From a practical perspective, the study demonstrates the value of an integrated AI ecosystem approach—combining knowledge graphs, generative AI, and learning analytics—over isolated implementations of single AI tools. The synergistic effects observed across all three modules suggest that the greatest pedagogical gains emerge when AI technologies are designed as interconnected components of a coherent learning architecture rather than as independent add-ons. The technical infrastructure developed in this study—comprising open-source NLP tools (spaCy), a community-edition graph database (Neo4j), and a fine-tuned open-source large language model—is designed for cost-effective deployment, with total development cost approximately RMB 8,000, making it accessible for replication at other institutions. These findings provide practical guidance for educators seeking to integrate AI tools into database courses [15, 25].

Several limitations should be acknowledged. First, the quasi-experimental design limits causal inference. The absence of random assignment and the reliance on historical controls introduce potential confounding variables. Second, the pilot implementation was conducted within a single institution, and generalizability requires further validation. Third, the ethical implications of AI-generated synthetic datasets and student data analytics warrant continued scrutiny.

5 Conclusions

This study has presented and evaluated a comprehensive AI-enabled teaching reform framework for the "Database Principles and Technology" course, targeting the specific challenges of database education for business-oriented majors. The proposed system integrates three AI-powered modules: a knowledge graph-driven theoretical teaching system, a generative AI-powered virtual scenario practical training platform, and a multimodal data-driven evaluation mechanism. The results of a two-semester pilot implementation at Hangzhou Normal University's Alibaba Business School demonstrate statistically significant improvements in students' conceptual knowledge acquisition (pre-post improvement of 16.2 percentage points), SQL coding proficiency (correctness rate from 68.3% to 86.7%), and learning engagement.

The contributions of this study are threefold. Theoretically, it extends the application of AI in higher education to the underexplored context of database education for non-technical business majors, grounding the analysis in cognitive load theory, situated learning theory, and formative assessment frameworks. Practically, it provides a replicable and cost-effective blueprint for integrated AI-enabled curriculum reform. Methodologically, it demonstrates the value of a mixed-methods action research design for evaluating complex educational technology interventions.

Future research directions include longitudinal studies tracking students' career outcomes, comparative studies across multiple institutional contexts, integration of multimodal large language models for enhanced personalization, and extension of the reform framework to other technically demanding courses within business curricula. As large language models continue to advance, their integration with domain-specific knowledge graphs offers significant potential for transforming technical education for non-computer science majors.

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