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AI-enabled smart teaching: empirical research based on knowledge graphs and learning profiles for university chemistry

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Abstract: Against the backdrop of digital transformation in education, smart teaching has become an important trend in the reform of higher engineering education. College chemistry features systematic content, abstract concepts, and tight logical connections. Traditional blended teaching, however, still falls short in process supervision, learning status diagnosis, and personalized support. This study combined knowledge graphs, learning profiles, and intelligent teaching assistants to build an integrated smart teaching model, and conducted a quasi-experiment with 277 engineering students. Results show that the experimental group performed notably better than the control group in learning task completion rate and mastery of difficult and key knowledge points. Both groups achieved a pass rate of over 96%, but the experimental group demonstrated distinct advantages in learning equity, process management, and precise tutoring. This model can effectively optimize learning paths, enhance process guidance, and promote knowledge internalization, providing empirical references for the smart teaching reform of basic science and engineering courses in universities.

Keywords: AI-assisted teaching; smart teaching; university chemistry; knowledge graph; empirical study

1 Introduction

Against the backdrop of advancing digital transformation in higher education, smart teaching has become an important approach to tackling challenges in large-class teaching and improving the quality of foundational courses [1]. It is characterized by data-driven instruction, precise adaptation and personalized support for students. As a core foundational course for engineering and agricultural majors, university chemistry involves numerous knowledge points, abstract microscopic concepts and tight logical connections, which imposes high requirements on students to construct a systematic knowledge framework. Traditional blended teaching is usually delivered at a unified pace, making it difficult for instructors to fully grasp students' actual performance in pre-class preparation and after-class review, and to identify their knowledge gaps in a timely manner for effective guidance. When learning complex principles and challenging content, students tend to acquire fragmented knowledge, and lack learning initiative, along with low completion rates of challenging tasks, which eventually result in significant disparities in learning effectiveness.

The advancement of technologies including artificial intelligence, knowledge graphs and learning profiles has provided new insights into addressing these issues [2]. The integration of artificial intelligence and education is no longer confined to single-function applications, instead, it has gradually evolved toward the innovation of holistic teaching models, with relevant research on intelligent evaluation, adaptive learning and precise intervention steadily advancing [3][4]. Existing studies have shown that technology integration can improve the efficiency of teaching feedback and extend effective learning time, which to some extent alleviates the practical dilemma of large-class teaching, where teachers face energy constraints and struggle to meet the personalized learning needs of every student. Knowledge graphs visualize the hierarchical structure and internal connections of knowledge points, helping reduce students' cognitive load and supporting them in constructing a more systematic knowledge framework [5], thus demonstrating promising application potential in structurally intensive disciplines such as chemistry and physics. Learning profiles depict student characteristics through multi-dimensional data on learning behaviors and academic performance via learning analytics, providing strong support for differentiated teaching, precise diagnosis and personalized instruction [6].

Although existing research has validated the educational value of the aforementioned technologies, several limitations still exist. Most studies on knowledge graphs focus on construction approaches and functional design, and few long-term empirical studies have been carried out in authentic classroom settings combined with learning profiles. Although learning profiles enable the diagnosis of students' learning status, a fully implemented practical model that links the identification of knowledge gaps with closed-loop teaching interventions has yet to be established in university chemistry instruction. Within the literature on university chemistry teaching reform, blended learning, flipped classrooms, and experimental teaching optimization have been widely investigated. Nevertheless, research that systematically integrates knowledge graphs, learning profiles, and AI teaching assistants through large-sample controlled experiments remains relatively scarce.

In view of the above practical problems and research gaps, this study takes the engineering-oriented university chemistry course as the research object, and constructs a smart teaching model integrating knowledge graphs, learning profiles and AI teaching assistants. A quasi-experimental design is adopted to examine its actual effects on students' learning behaviors, knowledge mastery and academic performance. This study aims to provide feasible practical schemes and empirical evidence for the smart teaching reform of chemistry and similar science and engineering foundational courses in higher education.

2 Research design and methodology

This study adopted a quasi-experimental design with four regular classes of University Chemistry for engineering majors at Henan Agricultural University as research participants, with a total sample size of 277 students. Students were assigned to two groups based on the teaching model. The experimental group included 158 students from Agricultural Engineering Class 25 and Electronic Information Class 25, who received an AI-supported smart teaching model integrated with knowledge graphs and learning profiles. The control group included 119 students from Energy and Power Engineering Class 24 and Transportation Class 24, who received traditional online-offline blended teaching. Both groups were taught by the same instructor, with identical syllabi, course content, class schedules, assessment methods and grading rubrics to control for confounding factors.

Student performance was assessed using a composite score, in which coursework accounted for 40% and the final written exam accounted for 60%. Data were primarily collected from the Chaoxing Learning Platform, including learning behavior records, task completion rates, mastery levels of key and difficult knowledge points, knowledge graph usage logs, AI teaching assistant intervention records, as well as composite grades and final exam scores. Descriptive statistics and between-group comparisons were conducted to evaluate the effects of the two teaching models in terms of learning engagement, knowledge mastery and academic performance.

3 Construction of the AI-assisted smart teaching mode

This study constructs a smart teaching model underpinned by knowledge graphs as the knowledge framework, learning profiles as the diagnostic basis, and AI teaching assistants as the implementation tool, forming a complete closed teaching loop consisting of structured knowledge presentation, precise learning status diagnosis, personalized intervention delivery, learning outcome feedback, and dynamic adjustment of teaching strategies. Based on the curriculum requirements and core content of university chemistry, this study constructed a knowledge graph comprising 319 knowledge points and 90 logical relationships. Among them, 149 points were linked with relevant learning resources, and 98 points were marked with corresponding difficulty and importance levels, leading to an overall construction rate of 46.71%. This knowledge graph provides support for pre-class preview, in-class explanation of key and difficult points, post-class review, as well as personalized resource recommendation. Leveraging multi-dimensional learning behavior data obtained from the learning platform, individual and class-level learning profiles were generated from four aspects: learning engagement, task completion, knowledge mastery, and weak point distribution. These profiles lay a foundation for teachers to carry out differentiated teaching and targeted guidance. The AI teaching assistant supports automatic scoring, real-time Q&A, learning progress reminders, intelligent recommendation of exercises and micro-lectures by knowledge points, and class learning analysis reports. These functions improve the efficiency of teaching feedback and reduce the repetitive workload of teachers, while ensuring timely and precise teaching interventions. In summary, the model takes knowledge points as its basic units, formulates targeted intervention strategies based on learning profiles, and implements supportive activities with AI teaching assistants, thereby achieving a more precise, personalized, and systematic teaching process.

4 Results and discussion

4.1 Learning behavior and task completion

The experimental group reached an overall learning task completion rate of 99.15%, while the rate in the control group was only 50.20%, representing a gap of 48.95 percentage points. For difficult knowledge points, completion rates were 97.56% and 45.38% in the two groups, a difference of 52.18 percentage points. In terms of exam-focused content, the experimental group also achieved a completion rate of 97.55%, whereas the control group stood at 56.23%, 41.32 percentage points lower. These findings show that smart teaching effectively improves student engagement and task completion, and mitigates typical problems in traditional instruction, such as low task completion, avoidance of difficult content, and insufficient process monitoring. Knowledge graphs organize knowledge in a structured and visual way, connecting scattered points into a unified system. This helps reduce students' cognitive pressure, clarify learning routes, and ease anxiety when facing complex content. Meanwhile, instant feedback and progress reminders from the AI teaching assistant strengthen ongoing guidance and help students maintain steady progress, making up for the result-oriented bias in traditional teaching.

4.2 Knowledge mastery

In terms of core knowledge grasp, the experimental group achieved an 86.82% mastery rate for exam-focused points, much higher than the 63.24% in the control group, an improvement of 23.58 percentage points. The mastery rate of key knowledge points reached 76.95% in the experimental group and 70.19% in the control group. For difficult points, the rates were 80.30% and 74.49%, respectively. Such results imply that smart teaching helps students better understand key content and internalize knowledge by identifying learning gaps and providing targeted support. Learning profiles allow instructors to track and diagnose learning progress continuously via multi-dimensional behavioral data, supporting data-based interventions over purely experience-based decisions. Through personalized practice and micro-lectures recommended by the AI assistant, teaching becomes more targeted and effectively enhances students' knowledge acquisition. By contrast, traditional blended teaching rarely enables detailed learning diagnosis and typically adopts uniform instructional strategies, which limits students' mastery of challenging content.

4.3 Academic performance

The experimental group achieved an average comprehensive score of 72.69 with a pass rate of 97.47%, whereas the control group had an average score of 78.97 with a pass rate of 96.63%. In the final written exam, the experimental group averaged 65.25 with a pass rate of 64.52%, compared with 72.24 and 88.19% in the control group. Both groups maintained high pass rates, meaning both teaching methods can meet the basic requirements of the course. The control group achieved higher final exam scores, which reflects the focus of traditional teaching on intensive final review. The experimental group, however, showed more stable learning progress and better instructional inclusiveness. The relatively high final exam scores in the control group may stem from the exam-oriented feature of traditional blended teaching, which improves performance through short-term intensive practice. Stronger process indicators in the experimental group reflect more gradual and balanced deep learning, which aligns better with the higher education goal of fostering independent learning and application abilities. This reflects an important advantage of smart teaching: it not only enhances knowledge mastery but also helps students develop sustainable learning competencies.

5 Conclusion

Overall, the intelligent teaching model combining knowledge graphs, learning profiles and AI teaching assistants performs well in college chemistry teaching. It significantly improves task completion rate and classroom participation, helps students master key examination content and difficult points more effectively, and supports a more balanced learning process. While both teaching models ensure high course pass rates, the intelligent approach demonstrates more distinct advantages in process monitoring, targeted intervention and fostering overall progress for all students, making it well-suited for application and promotion in chemistry and other basic science and engineering courses. The results also suggest directions for smart education reform: For basic courses, we can further optimize the knowledge structure, strengthen the collection and analysis of learning data, apply intelligent tools to improve teaching precision, and gradually shift from uniform teaching to student-centered personalized instruction.

Empirically, this study offers a feasible implementation framework for smart teaching and provides a replicable model for the application of artificial intelligence in basic science and engineering courses. However, some limitations exist: the knowledge graph does not cover the entire curriculum, analyses of students' learning experience and cognitive development remain superficial, and the sample is limited to one university, so the generalizability of the conclusions requires further validation. In future research, the structure of knowledge graphs and learning profile diagnosis models can be further optimized, and multi-institutional and cross-disciplinary experiments can be conducted to facilitate the deeper and broader application of intelligent teaching in science and engineering courses.

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Conflicts of interest

The author declares no conflicts of interest regarding the publication of this paper.

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