ISSN 2522-6398 Vol. 8, Issue 11: 28-34, DOI: 10.25236/FER.2025.081104

Exploring the Application of Artificial Intelligence Techniques in Teaching the Sustainable Energy Materials Course

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Abstract: *With the rapid advancement of artificial intelligence (AI) technologies, higher education is undergoing a profound transformation. As a core component of the emerging engineering discipline in materials science, the course, Sustainable Energy Materials (SEM) integrates interdisciplinary knowledge and cutting-edge research, presenting new challenges for teaching innovation. This study, conducted during one semester of the 2024-2025 academic year, proposes an AI-enhanced instructional framework incorporating intelligent learning assistance, personalized recommendation, and virtual experiment simulation. Through comparative group surveys and quantitative data analysis, significant improvements were observed in students' learning engagement, knowledge mastery, and innovation competence under the AI-assisted model ($p<0.05$). Pearson correlation analysis further revealed strong positive relationships between AI system usage and learning performance ($r=0.70–0.85$, $p<0.001$). These findings demonstrate that AI-driven pedagogical integration can effectively promote active learning and higher-order cognitive development. The approach provides a feasible pathway for reforming sustainable energy courses, offering valuable insights into data-driven, student-centered teaching designs in the context of intelligent education.*

Keywords: *Artificial Intelligence; Sustainable Energy Materials; Intelligent Learning Assistance; Teaching Innovation; Higher Education Reform*

1. Introduction

With the rapid advancement of information technologies, artificial intelligence (AI) and big data are profoundly transforming teaching models and learning ecosystems in higher education. In materials science and sustainable energy education, traditional lecture-based and memory-driven approaches can no longer meet students' increasing demand for interactive, flexible, and personalized learning. The Sustainable Energy Materials (SEM) course embodies highly interdisciplinary content—covering solar cell materials, energy-storage electrodes, and photocatalytic materials—with fast-evolving knowledge and complex theoretical frameworks that pose new pedagogical challenges. However, persistent issues such as insufficient student motivation, fragmented knowledge acquisition, low classroom engagement, and underdeveloped experimental or engineering skills continue to hinder students' comprehensive understanding and innovation capacity. To address these limitations, this study integrates AI and big data technologies into the SEM course to develop an intelligent, hybrid teaching model that supports personalized learning through pre-class preparation, in-class interaction, and post-class consolidation.

This instructional innovation also aligns with broader national and educational trends. In 2024, China's Government Work Report proposed to "deepen the research and application of big data and artificial intelligence, and carry out the 'AI+' initiative, explicitly encouraging the integration of AI with education[1]. Within higher education, AI has rapidly emerged as a central driver for transforming teaching models and improving learning outcomes[2]. The deep convergence of AI and education forms a multidimensional, highly coupled system spanning teaching, learning, assessment, research, and management, and extending across sub-dimensions such as instructional design, pedagogical philosophy, and precision-driven research[3-5]. Building upon this policy momentum and theoretical foundation, numerous scholars have further examined the integration of AI and education from policy, theoretical, and practical perspectives. Zhu et al. argued that AI-based learning models are reshaping traditional instruction by fostering collaborative, inquiry-oriented, and intelligent teaching modes[6]. Ke et al. emphasized that AI can comprehensively enhance teaching, learning, and assessment by improving instructional quality and efficiency[7]. Liu et al. explored the challenges of AI-driven educational innovation, including reconceptualizing the essence of education, managing human-AI co-intelligence, meeting infrastructural demands, and addressing ethical and fairness concerns[8]. Xing et al. conducted a comparative study of AI application frameworks at 35 leading U.S. universities, highlighting both achievements and limitations in institutional implementation and underscoring the necessity of rigorous evaluative mechanisms for AI-enabled pedagogy[9]. Against this backdrop, the present study empirically examines the effectiveness of AI-enabled instruction in SEM education, offering practical insights for the intelligent transformation of engineering courses.

Against this backdrop of accelerating AI-education integration, a critical gap remains in understanding how artificial intelligence can be effectively embedded into the pedagogical design of specialized engineering and applied science courses. Although prior studies have mainly addressed policy frameworks and institutional implementations, less attention has been given to course-specific instructional models that connect AI technologies with disciplinary knowledge and practical skill development. Addressing this gap, the present study develops and empirically validates an AI-enhanced instructional framework for the SEM course. The framework integrates three key components—an Intelligent Teaching Assistant System that provides adaptive instructional support, a Personalized Learning Path Recommendation module that guides individualized learning progression, and an AI-Driven Experimental Simulation Platform that enhances experiential and innovative learning. The subsequent sections elaborate on the conceptual design, technological realization, and pedagogical contribution of each component, outlining how they collectively advance an AI-integrated learning environment tailored to applied science education.

2. Methods

2.1 Intelligent Teaching Assistant System

An AI-powered Intelligent Teaching Assistant was integrated into the Sustainable Energy Materials course to provide interactive cognitive support beyond the classroom. The system assists students with post-class question-answering, literature recommendations, and conceptual clarification of complex topics. Through natural language interaction, students can obtain immediate, context-relevant explanations and adaptive learning guidance. This intelligent support not only reduces teachers' routine workload but also promotes active knowledge construction and continuous engagement in self-directed learning. In addition, the assistant was connected to the university's learning management system to monitor student inquiry patterns and feedback trends. These data were analyzed to identify common conceptual bottlenecks, allowing instructors to refine instructional materials and adjust teaching strategies dynamically.

2.2 Personalized Learning Path Recommendation

The course employed a personalized learning analytics module that utilizes students' pre-test scores and ongoing activity data to model individual learning profiles. Through a combination of K-means clustering and decision-tree analysis, students were categorized according to learning styles, knowledge mastery, and engagement characteristics. The K-means algorithm partitions learners into k clusters by minimizing the sum of squared deviations between individual feature vectors and their respective cluster centroids, as expressed in Equation (1):

$$\mathbf{J} = \sum_{\mathbf{i}=\mathbf{1}}^{\mathbf{k}} \sum_{\mathbf{x_j} \in \mathbf{c_i}} \left\| \mathbf{x_j} - \mathbf{u_i} \right\|^2 \tag{1}$$

Where J denotes the total within-cluster variance to be minimized; k is the number of clusters; x_j represents the j-th learner's feature vector (including indicators such as pre-test scores, quiz performance, participation frequency, and resource interaction time); C_i is the set of learners assigned to the i-th cluster; μ_i is the centroid of cluster i, computed as the mean vector of all learners' features within that cluster.

The resulting clusters were then fed into a decision tree model to identify key predictors of learning

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performance and engagement patterns, forming the basis for adaptive instructional design. Based on the classification outcomes, the system automatically generated personalized learning pathways, adaptive resource recommendations, and differentiated task difficulty levels. This data driven approach enabled teachers to move from uniform instruction toward precision teaching, ensuring that high achieving students were continuously challenged while providing targeted support for learners who struggled with key SEM concepts. Consequently, the AI based recommendation system enhanced learning efficiency, reduced cognitive overload, and improved the alignment between instructional design and learner diversity.

2.3 AI-Driven Experimental Simulation Platform

The course incorporated an AI-driven experimental simulation platform designed to enhance students' ability to conduct data-oriented materials analysis and virtual experimentation. The platform integrates machine learning models trained on empirical datasets of energy materials to predict key physicochemical properties such as electrode specific capacity, ionic conductivity, and band-gap energy. Within the interface, students can define compositional or structural parameters as inputs, execute model-based predictions, and visualize performance outcomes in real time. Iterative optimization functions allow learners to adjust variables and observe corresponding property changes, guiding them toward identifying optimal material configurations. This simulation environment serves as a pre-experimental stage, enabling students to validate hypotheses and refine design strategies before conducting physical experiments. By combining predictive analytics with virtual prototyping, the platform effectively reduces laboratory trial-and-error, experimental costs, and safety risks. Additionally, the interactive modeling process reinforces students' understanding of structure-property correlations in sustainable energy materials while fostering computational analysis skills applicable to future research and innovation.

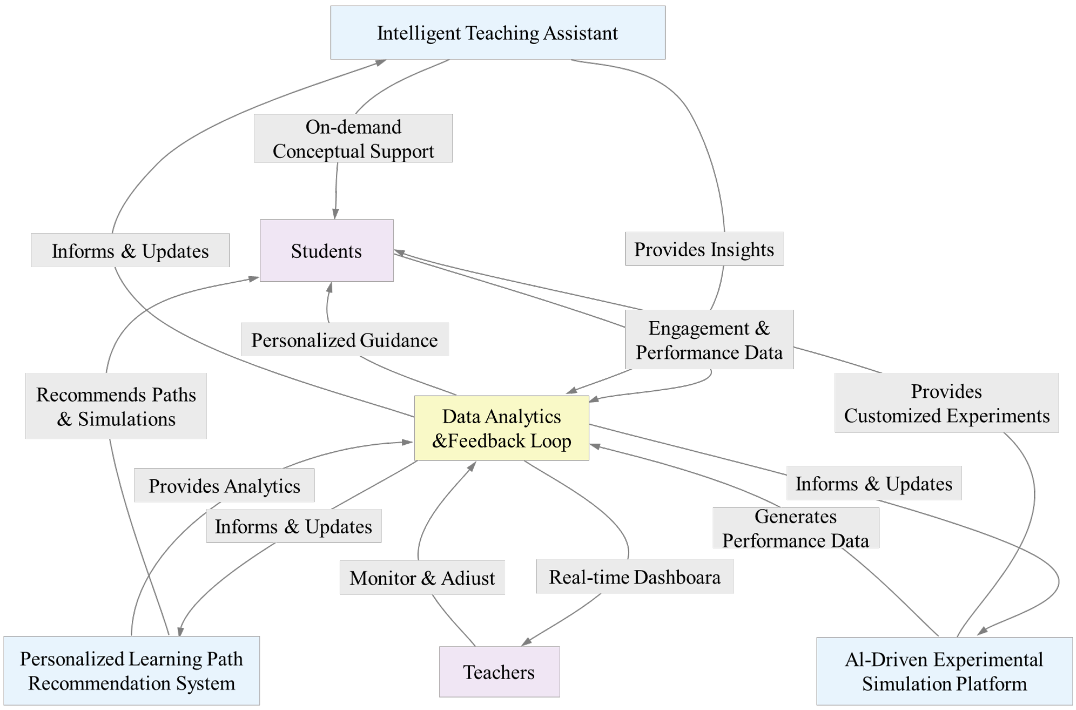

Figure 1 Overview of the interconnected AI-assisted teaching framework integrating the Intelligent Teaching Assistant, Personalized Learning Path Recommendation System, and AI-Driven Experimental Simulation Platform for adaptive SEM learning.

The three AI-enabled components—the Intelligent Teaching Assistant, the Personalized Learning Path Recommendation System, and the AI-Driven Experimental Simulation Platform—functioned as an interconnected ecosystem that collectively enhanced the SEM teaching and learning process in Figure 1. The Intelligent Teaching Assistant provided on-demand conceptual support based on insights derived from the personalized analytics module, forming a continuous feedback loop that strengthened students' conceptual mastery and metacognitive regulation. Analytical outputs from the personalized learning system also guided the customization of virtual experiments in the simulation platform; for example, students with lower performance in electrochemical kinetics were directed toward parameter-specific simulations on reaction rates and charge transfer processes. Through these interconnections, theoretical

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learning, data analytics, and experimental practice were dynamically integrated. Teachers were able to monitor learning patterns via real-time dashboards and adjust instruction accordingly, while students experienced a coherent progression from knowledge acquisition to application and innovation. This multi-layered synergy transformed the course into a data-informed, adaptive learning ecosystem, with AI serving as both a cognitive partner and an instructional catalyst, ultimately fostering deeper learning, sustained engagement, and independent inquiry.

3. Results and Discussion

3.1 Research Design and Grouping

To assess the effectiveness of AI-assisted teaching in the Sustainable Energy Materials course, a quasi-experimental design was implemented over a 16-week semester. Sixty third-year undergraduate students majoring in Materials Science were randomly divided into two groups:

● Experimental Group (A, n=30): received AI-supported instruction integrating the Intelligent Teaching Assistant, Personalized Path Recommendation, and AI-Driven Simulation Platform.

● Control Group (B, n=30): received conventional teacher-centered instruction with no AI enhancement.

Both groups were taught by the same instructor and followed identical syllabus content and assessment rubrics to ensure internal validity.

3.2 Data Collection and Evaluation Indicators

Four main dimensions were used to evaluate learning effectiveness: learning motivation, knowledge mastery, self-regulated learning ability, and innovation competence (Table 1). Data sources included pre-/post-tests, questionnaires (5-point Likert scale), in-system learning analytics, and student interviews (Table 2). To ensure comprehensive evaluation, both subjective and objective indicators were employed. The questionnaire and survey items captured learners' perceptions and behavioral tendencies, whereas test scores and project evaluations reflected actual performance outcomes. Different measurement types were selected according to the nature of each construct, while later analyses normalized all scores for cross-dimension comparison.

Table1: Research Dimensions and Corresponding Measurement Indicators

Dimension	Description	Data Source	Measurement Type
Learning Motivation	Interest and persistence in course learning	Questionnaire	1-5 Likert
Knowledge Mastery	Conceptual and procedural understanding	Tests	Scores (0-100)
Self-Regulated Learning	Planning, monitoring, reflection ability	Survey	1-5 Likert
Innovation Competence	Creativity and problem-solving capacity	Project Evaluation	1-5 Rubric

3.3 Quantitative Findings

3.3.1 Descriptive Statistical Results

Table 2: Comparison of Pre-test and Post-test Results Between AI-Assisted and Traditional Teaching Groups

Indicator	Group	Pre-test Mean	Post-test Mean	Improvement (%)
Learning Motivation (1-5)	A (AI)	3.28	4.67	+42.4
	B (Traditional)	3.31	3.95	+19.3
Knowledge Mastery (0-100)	A (AI)	65.7	88.1	+34.1
	B (Traditional)	66.2	78.5	+18.6
Self-Regulated Learning (1-5)	A (AI)	3.12	4.45	+42.6
	B (Traditional)	3.10	3.74	+20.6
Innovation Competence (1-5)	A (AI)	3.05	4.62	+51.5
	B (Traditional)	3.07	3.83	+24.8

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3.3.2 Visualization of Learning Performance

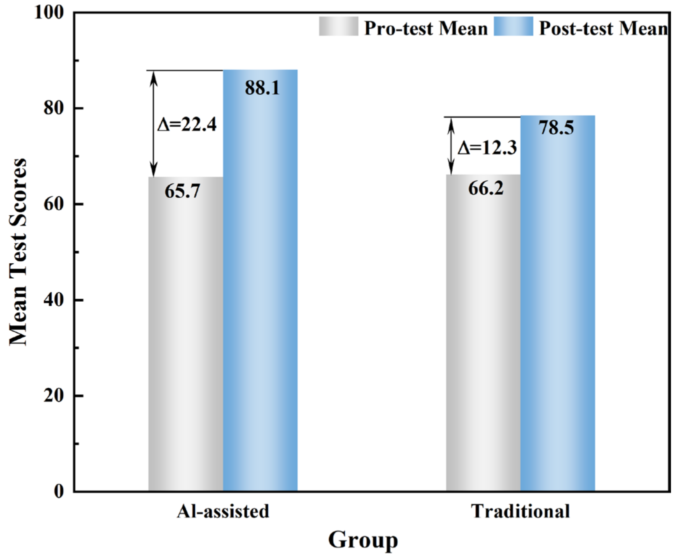

Figure 2 Comparison of pre-and post-test knowledge mastery between groups.

Note: Data based on mean test scores (n=30 per group).

Figure 2 illustrates the comparative improvement in knowledge mastery between the AI-assisted and traditional groups. The bar chart reveals that both groups experienced progress during the semester; however, the experimental group achieved a mean score increase of 22.4 points, nearly 1.8 times greater than that of the control group. Figure 3 depicts the distribution of learning motivation improvement across both cohorts. The histogram shows that 83% of students in the AI group reported motivation ratings of 4 or above after the intervention, compared to 52% in the control group. The upward shift in the AI group's overall distribution confirms the positive emotional and engagement impact of the AI-supported learning environment.

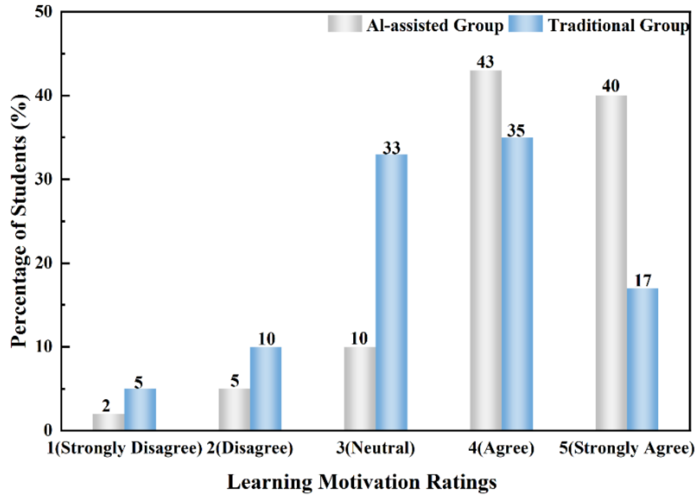

Figure 3 Distribution of learning motivation ratings after AI-supported instruction.

Note: Values derived from post-course questionnaire responses (5-point Likert scale).

3.4 Statistical Significance and Correlation Analysis

Independent samples t tests confirmed that the AI assisted and traditional groups differed significantly across all four learning dimensions ($p<0.05$). Pearson correlation analysis further revealed strong positive relationships among key variables (Figure 4).

- AI system usage frequency×knowledge mastery: $r\approx0.85$ (**strong**, $p<0.001$**)
- AI interaction count×innovation competence: $r\approx0.78$ (**strong**, $p<0.001$**)

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● Personalized path adherence×self-regulated learning: r≈0.70 (**moderate-to-strong**, $p < 0.001$**)

These findings demonstrate that higher levels of engagement with AI resources were significantly associated with better learning performance.

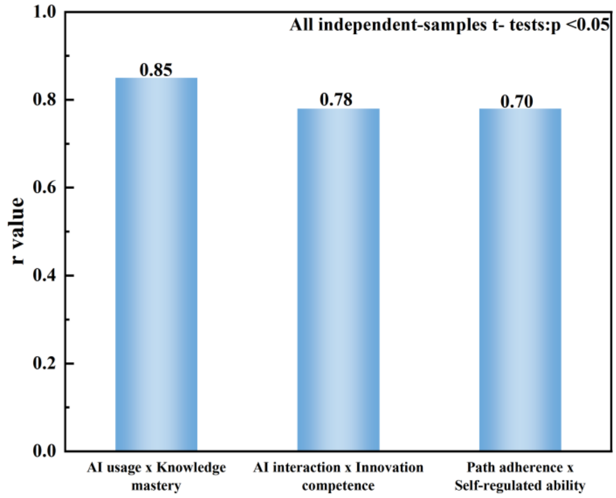

Figure 4 Relationships among AI utilization behaviors and student learning performance.

3.5 Qualitative Insights from Interviews

Semi-structured interviews provided additional evidence of behavioral and cognitive improvement:

• "The AI Assistant gave me immediate answers and guided me toward relevant research papers, saving time and deepening my understanding."

• "The personalized recommendations kept me working on topics that matched my progress level. It prevented me from falling behind."

• "The simulation platform helped me test energy-storage models virtually, which made my lab results more predictable."

Thematic coding of responses identified three high-frequency terms—"efficiency" (78%), "motivation" (72%), and "confidence" (68%)—further validating the quantitative results.

3.6 Comprehensive Evaluation of Learning Effectiveness

From a multi-dimensional standpoint, the AI-enabled model demonstrated substantial advantages over traditional approaches:

• Cognitive Gains: Through adaptive content delivery and real-time feedback, students achieved stronger concept retention.

• Affective Enhancement: Intelligent assistants increased enjoyment, engagement, and emotional connection to the course.

• Metacognitive Growth: Personalized analytics empowered learners to plan, monitor, and reflect on their progress.

• Creative Development: The AI simulation platform provided an authentic research-like environment, nurturing innovation and experimentation.

Collectively, these findings confirm that AI technologies significantly improved students' academic achievement, engagement, and autonomous learning behaviors in the SEM course. The inclusion of visual analytics (Figures 1-3) further substantiates the measurable transformation brought about by AI-enabled pedagogy.

4. Conclusion

This research verified the positive impact of AI-assisted teaching on the Sustainable Energy Materials

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course. The independent-samples t-test confirmed significant differences between the AI-assisted and traditional groups across four learning dimensions, indicating enhanced outcomes in knowledge acquisition, innovation, and self-regulated learning. The survey data and correlation analysis further supported that students who engaged more actively with AI resources achieved higher cognitive performance and demonstrated greater creativity in experimental design. In the future, broader applications of AI technologies—such as adaptive assessment, real-time learning analytics, and immersive virtual laboratories—are expected to further personalize the learning process and bridge the gap between theoretical understanding and practical application. Continuous optimization of AI-based teaching platforms and deeper cross-disciplinary integration will be crucial to achieving sustainable development in materials science education and beyond.

Acknowledgement

This work was supported by the Faculty Development Research Project of the University of Shanghai for Science and Technology (CFTD2025YB24, supervised by Zhuo Wang) and by the Shanghai University Young Teachers Training Key Program (10-24-112-005-043, supervised by Jia Yi Jin).

References

[1] The State Council of the People's Republic of China. Government Work Report. Retrieved October 27, 2024, from https://www.gov.cn/gongbao/2024/issue_11246/202403/content _6941846. html.
[2] Zhao, Y., Xu, D., Liu, Z., Wang, H. Cultivating future engineering talents in automation driven by "OODA + AI": A case study of the College of Intelligent Science and Engineering, Harbin Engineering University[J]. Research in Higher Engineering Education, 2025(1), 61-67.
[3] Li Kuan, Wang Wenping. The innovative development of education and teaching management in higher universities under the background of artificial intelligence [J]. Science and Technology Information, 2022, 20 (9): 187-190.
[4] Guan, Z., Dong, J., Xu, X. AI-empowered course development and teaching innovation in "Automatic Control Principles"[J]. China Electric Power Education, 2025, (2), 70-71.
[5] Zhang S. Practice of Hybrid teaching of advanced mathematics based on artificial intelligence[J]. Frontiers in Educational Research, 2025, 8(8), 113-120.
[6] Wei, F., Yang, K., Zhu, Z. Collaborative inquiry and intelligent creation: A new learning model in the era of generative artificial intelligence[J]. Open Education Research, 2025, 31(2), 14-23.
[7] Ke, Q., Huang, C., Li, F. AI-empowered professional development of teachers under the construction of an education-powerful nation[J]. Journal of Guangzhou Open University, 2024, 24(5), 9-15.
[8] Liu, S., Hao, X. Generative artificial intelligence for educational innovation: Challenges and approaches[J]. Tsinghua Journal of Education Research, 2024, 45(3), 1-12.
[9] Xing, Y., Qian, L. Reform actions and reflections of top American universities in response to AI-based teaching applications[J]. Open Education Research, 2025, 31(2), 24-35.