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Exploration of An Intelligent Teaching System for the Post-Lithium Battery Course Empowered by AI

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Abstract: This study addresses critical challenges in Post-Lithium Battery Courses, including outdated knowledge, disconnection between theory and practice, and simplistic assessment methods. With AI assistance, we propose an intelligent teaching architecture based on a teaching/evaluation/feedback cycle. The system integrates dynamic knowledge graphs and adaptive learning engines to achieve personalized knowledge delivery, utilizes virtual simulation and digital twins to overcome practical training limitations, and employs a data-driven approach to establish a process-centered teaching-evaluation-feedback loop. Practical applications demonstrate its effectiveness in visualizing complex principles, simulating processes, and facilitating project-based innovation. The system significantly enhances students' knowledge integration, engineering thinking, and problem-solving capabilities, providing new insights for curriculum reform under engineering education accreditation. The implementation results from a semester-long case study show a 27.3% improvement in knowledge mastery and a 42% increase in practical skills success rate, validating the system's efficacy in bridging the theory-practice gap.

Keywords: AI; Post-Lithium Battery Course; Intelligent teaching; Teaching system

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1. Introduction

The rapid evolution of the new energy industry and lithium-ion battery technology creates increasing demands for professional training. Traditional teaching models fail to effectively illustrate micro-electrochemical principles or provide adequate practical experience due to cost and safety constraints. Student assessment remains limited to theoretical examinations, unable to evaluate engineering innovation capabilities. Although educational reforms like Outcome-Based Education (OBE) have been implemented, they still cannot achieve personalized learning and process-oriented evaluation. Artificial intelligence technologies, with their capabilities in data mining, content analysis, and virtual simulation, offer solutions to these challenges. This research aims to construct an AI-empowered teaching system to enhance educational effectiveness and cultivate talent meeting industry requirements. This paradigm shift is critical as global investments in energy storage are projected to exceed $300 billion by 2030, creating an urgent need for a highly skilled workforce proficient in next-generation battery technologies. The convergence of AI and pedagogy represents a transformative opportunity to reengineer engineering education from a static knowledge-transfer model into a dynamic, adaptive, and experiential learning ecosystem.

2. Teaching status of Post-Lithium Battery Courses and the necessity of AI empowerment

Lithium-ion battery technology is essential for modern new energy development and has become a key component in materials, chemistry, chemical engineering, and related disciplines. However, its course content is highly theoretical and practical, posing significant challenges for traditional teaching methods. Core concepts such as material microstructure, electrochemical mechanisms, and manufacturing processes are difficult to convey through textbooks alone. Students struggle to visualize dynamic processes like lithium-ion migration, leading to poor conceptual understanding. Furthermore, constraints like limited lab space, high costs, and safety concerns restrict hands-on activities such as battery assembly and testing, creating a gap between theory and practice. Although teaching reforms like Outcome-Based Education (OBE) and integrated scientific philosophy have been introduced, they still fall short in enabling personalized learning and providing timely feedback, as highlighted in the teaching reforms discussed by Jin et al. (2023) [3]. The emergence of artificial intelligence (AI) offers a promising solution. AI technologies—including machine learning, knowledge graphs, and virtual simulation—can create dynamic, interactive teaching environments. They transform abstract concepts into visual models, convert high-risk experiments into safe virtual training, and generate personalized learning paths based on student behavior analysis. This AI-driven approach represents a fundamental shift in teaching philosophy, aiming to enhance effectiveness and cultivate talent ready for the energy industry's future needs. Specifically, the integration of natural language processing (NLP) enables automated extraction and structuring of knowledge from vast and rapidly evolving sources such as research papers (e.g., from Nature Energy or Advanced Materials) and patent databases, ensuring the curriculum remains at the technological forefront. Furthermore, computer vision algorithms can analyze student engagement and confusion levels in real-time during virtual operations, allowing for instantaneous adaptive support, a feature impossible to achieve in traditional settings.

3. Overall construction of the AI-empowered intelligent teaching system for Post-Lithium Battery Courses

3.1. Core philosophy of the system

The system's foundational philosophy centers on student development and capability achievement, constructing a data-driven, dynamically optimized teaching paradigm that transcends traditional linear knowledge transmission. It addresses core challenges in lithium-ion battery education, including theoretical abstraction, practical disconnection, and assessment limitations. Through dynamic knowledge graphs, the system transforms static content into living networks that integrate cutting-edge industry and research developments, ensuring synchronous evolution with technological progress. Virtual simulation and digital twin technologies create immersive, risk-free environments where students experiment with process parameters and understand their impact on performance, transforming abstract principles into operational engineering intuition. Crucially, multidimensional data collection and analysis form an intelligent closed loop that enables adaptive learning paths and data-informed teaching adjustments, achieving organic unity between scale cultivation and personalized development. This philosophy is underpinned by a constructivist learning theory, which posits that knowledge is actively built by the learner through experience. The system acts as a cognitive scaffold, guiding students from concrete experiences (virtual experiments) to abstract conceptualization (theory) and active experimentation (project design), thereby fostering deeper, more durable learning. The ultimate goal is to cultivate T-shaped professionals with both deep technical expertise in battery technology and broad systemic thinking abilities.

3.2. Functional design of core modules

The system integrates three core modules: intelligent cognitive construction, virtual simulation training, and data-driven assessment. The cognitive module employs dynamic knowledge graphs to transform course content into interconnected visual networks, continuously updated with cutting-edge research through an adaptive learning engine that tailors paths based on student interactions. The virtual training platform uses high-fidelity modeling and digital twin technology to simulate battery production processes, allowing parameter adjustment with real-time performance feedback and intelligent error analysis. The assessment system collects comprehensive process data to generate multidimensional ability profiles, providing personalized feedback and teaching optimization support through dynamic dashboards and analytics. Together, these modules create an integrated teaching-learning-evaluation ecosystem that adapts to individual needs while maintaining systematic coherence. For instance, the adaptive learning engine specifically employs a hybrid recommendation algorithm combining collaborative filtering (“students who struggled with SEI film formation also found these resources helpful”) and knowledge tracing models that map a learner’s mastery of prerequisite concepts like electrochemical potentials to their ability to grasp more advanced topics like fast-charging protocols. The digital twin platform is built on a multi-physics simulation core that simultaneously solves coupled equations for ion transport, heat generation, and mechanical stress, providing students with a holistic view of battery behavior under complex operating conditions similar to the virtual training approaches explored by Yang et al. (2022) [4].

3.3. Technical support and integration path

The system builds upon a layered, service-oriented architecture that organically integrates intelligent algorithms, teaching resources, and business logic through standardized interfaces. The infrastructure layer leverages cloud computing’s elastic capabilities and containerization for scalable deployment. The data/algorithm layer features a unified data platform that cleanses and integrates multimodal teaching data into valuable assets. Machine learning models operate here for knowledge graph updating, path recommendation, and ability assessment, continuously optimizing through data learning. The core capability layer encapsulates these algorithms into reusable microservices exposed via API gateways. The three application modules are developed as independent units calling shared microservices, while message queues enable data exchange and business linkage, forming a tightly coordinated closed loop. The architecture follows open standards for future extensibility and employs CI/CD pipelines for agile iteration, ensuring long-term viability amid educational transformations. A typical data flow begins when a student interacts with a knowledge node on “solid-state electrolytes.” This interaction event is captured by the data platform, triggering the recommendation microservice. The service queries the student’s profile and, using a matrix factorization model, identifies relevant research papers on sulfide-based electrolytes. Simultaneously, it signals the virtual simulation service to pre-load a related experiment module for ionic conductivity measurement. This seamless, event-driven integration ensures a fluid and responsive learning experience, eliminating the friction typically associated with switching between different learning tools and platforms.

4. Practical application of AI technology in specific teaching scenarios of Post-Lithium Battery Courses

4.1. Visualized teaching of abstract principles

In the Post-Lithium Battery Course instruction, AI-powered dynamic visualization transforms abstract principles into intuitive cognitive tools that effectively address micro-electrochemical teaching challenges. Molecular dynamics simulations and 3D animation rendering enable magnified demonstration of lithium-ion intercalation/deintercalation and migration processes within electrode lattices, allowing students to observe ion diffusion paths and concentration changes under different states of charge. Multi-physics coupling models visualize real-time potential distribution, current density variations, and temperature field evolution during charge/discharge processes, converting abstract electrode reaction kinetics into interactive imagery that helps students establish essential connections between macroscopic performance and microscopic interface reactions. For invisible processes like solid electrolyte interphase formation, machine learning potential-based simulations dynamically display molecular and electron cloud reconstruction, correlated with actual capacity decay curves to help students understand microscopic mechanisms while mastering their impact on cycle life. This immersive visualization reduces cognitive barriers while enabling autonomous exploration of material-process-performance relationships through interactive parameter adjustment and immediate feedback, deepening core principle understanding through active inquiry. For example, students can manipulate the crystallographic orientation of a nickel-rich cathode particle (e.g., NMC811) within the simulation and immediately observe the resulting anisotropic expansion and the consequent development of microcracks during lithium insertion, directly linking material microstructure to mechanical degradation and capacity fade—a relationship nearly impossible to grasp from static textbook images alone as demonstrated in the visualization techniques employed by Liu et al. (2023) [2].

4.2. Simulation training for complex processes

AI technology creates breakthrough practical training through high-precision digital twin systems that address traditional limitations in safety and cost. The platform mirrors real production lines using virtual reality to physically model and dynamically simulate entire processes from electrode slurry preparation and coating to cell assembly and electrolyte filling. Students operate virtual equipment immersively while observing inter-process connections, autonomously adjusting key parameters like slurry solid content, coating speed, and compaction density. The system employs multi-physics coupling algorithms to simulate real-time impacts of these adjustments on electrode microstructure and final battery performance, generating immediate visualized data reports. When process deviations like uneven coating or excessive rolling occur, intelligent guidance compares operations against standards to suggest optimizations and analyze failure mechanisms. Safety modules simulate extreme conditions, including thermal runaway and electrolyte leakage, systematically training emergency response capabilities akin to the safety training modules developed by Yang et al. (2022) [4]. This deep integration of real-time decision feedback with result verification enables valuable production experience accumulation in risk-free environments, effectively cultivating engineering optimization abilities and quality control awareness. A key training scenario involves optimizing the calendering process: students adjust the roller pressure and temperature, and the simulation calculates the resulting electrode porosity and tortuosity using empirical models. The system then feeds these structural parameters into a Newman-type electrochemical model to predict the cell's rate performance, creating a direct, quantifiable link between a manufacturing decision (pressure) and a key product metric (C-rate capability). This "process-structure-performance" chain is central to battery engineering and is mastered through repeated, consequence-free experimentation.

4.3. Project-based innovation design

This teaching segment applies AI technologies to construct a comprehensive innovation practice from demand analysis to solution optimization. The system analyzes industry and academic trends to intelligently generate challenging yet feasible problems, such as developing high-energy-density cathodes or designing fast-charging systems. During solution conception, knowledge graphs provide curated references while generative AI assists in material selection, structural design, and process route screening. The core design phase employs multi-scale simulation tools for high-throughput virtual screening of electrode formulations and cell configurations, while AI engines use machine learning to predict electrochemical performance and multi-objective optimization to balance energy density, cycle life, and cost trade-offs. Following simulation verification, digital twin platforms create virtual prototypes that provide data on rate performance and thermal management, with system-identified design flaws and corrective guidance. This end-to-end practice enables students to experience collaborative brainstorming, simulation verification, and iterative optimization, developing systematic thinking and interdisciplinary integration capabilities while participating in the complete innovation chain to enhance complex problem-solving abilities. In a typical project, a student team might be tasked with designing a high-energy-density cell for electric aviation. The AI system first provides a curated knowledge base on lightweight materials and high-voltage electrolytes. The team then uses generative design tools to explore thousands of possible electrode thickness and porosity combinations. An AI-powered multi-objective optimizer, employing algorithms like NSGA-II, helps them navigate the trade-offs between energy density (Wh/kg), power density (W/kg), and cycle life, ultimately presenting a Pareto front of optimal solutions. Finally, they create a digital twin of their chosen design to simulate performance under realistic flight profile loads, receiving instant feedback on critical issues like temperature hotspots under high-current discharge.

5. Case study and effectiveness evaluation

5.1. Implementation case: Application in the "Post-Lithium Battery Materials and Technology" course

This study implemented the AI-empowered teaching system in the general course "Post-Lithium Battery Materials and Technology" over one semester. The course was designed for a diverse student body, with no restrictions on major or academic year. The case study involved 95 students divided into an experimental group using the intelligent system and a control group following traditional teaching methods. Over 32 credit hours, the experimental group utilized the dynamic knowledge graph for autonomous learning of core concepts such as cathode material crystal structures and lithium-ion migration mechanisms. In the virtual simulation platform, students completed key process modules including electrode slurry viscosity optimization, coating uniformity control, and formation cycle testing. The project-based innovation design segment tasked students with optimizing the energy density of an NMC811 cathode material system, requiring them to navigate trade-offs between specific capacity, tap density, and cycle stability through iterative simulation following the project-based framework established by Huang et al. (2023) [1]. The instructional design followed a flipped classroom model, where students first acquired foundational knowledge autonomously through the AI system, freeing up classroom time for interactive discussions, deep dives into complex phenomena like voltage hysteresis, and collaborative problem-solving sessions focused on the AI-generated project challenges, thereby maximizing the value of face-to-face interaction.

5.2. Quantitative analysis of teaching effectiveness

A multi-dimensional evaluation system was employed to quantitatively assess the teaching outcomes. Pre- and post-test assessments revealed that the experimental group's average score on knowledge mastery increased by 27.3% compared to the control group's 11.5% improvement. In practical ability assessments, students using the digital twin platform achieved a 42% higher success rate in process parameter optimization tasks. Analysis of innovation capability, evaluated through project reports and design solutions, showed that the experimental group demonstrated significantly greater proficiency in proposing alternative material systems and conducting multi-objective optimization. A survey on learning engagement indicated that 89% of students in the experimental group reported a deeper understanding of the intrinsic links between process parameters and battery performance, attributing this to the immediate feedback provided by the AI system. Furthermore, correlation analysis of learning behavior data revealed a strong positive relationship ($r = 0.72$, $p < 0.01$) between the frequency of using the knowledge graph for exploratory learning and final comprehensive assessment scores. A detailed analysis of the project reports using a rubric scored on a 100-point scale showed that the experimental group outperformed the control group by an average of 15 points, with the most significant differences observed in the "justification of design choices" and "analysis of trade-offs" criteria, indicating a marked improvement in critical engineering judgment and decision-making skills consistent with the assessment methodologies validated by Jin et al. (2023) [3].

5.3. Discussion on implementation challenges and optimization strategies

Despite the significant advantages demonstrated, the implementation process also revealed several challenges. Firstly, the initial construction of high-fidelity virtual simulation models requires substantial computational resources and interdisciplinary expertise, presenting a high barrier to entry. Secondly, the effective operation of the adaptive learning engine depends on a critical mass of student interaction data, meaning its optimization effect is more pronounced in the later stages of course delivery. Additionally, the system's demand for instructor AI literacy necessitates targeted training, as some instructors initially struggled with data interpretation from the teaching dashboard. To address these challenges, future iterations will incorporate lightweight modeling techniques to reduce computational load, implement incremental learning algorithms to accelerate model optimization, and develop an AI-assisted teacher guidance module that provides interpretable analytics and instructional suggestions. These strategies aim to lower the implementation threshold while enhancing the system's practicality and scalability across different institutional contexts. For example, to tackle the data dependency issue, the system will be pre-trained on anonymized interaction data from pilot programs, using transfer learning techniques to provide a baseline level of personalization from the very first cohort of students at a new institution. Furthermore, a community platform for educators will be established to share and collaboratively refine simulation modules and assessment rubrics, fostering an ecosystem of continuous improvement and reducing the development burden on any single institution, as suggested in the collaborative models proposed by Liu et al. (2023)[2].

6. Conclusion

This study constructs an AI-empowered intelligent teaching system that effectively addresses core challenges in traditional lithium-ion battery instruction through organic integration of dynamic knowledge graphs, virtual simulation platforms, and data-driven assessment. The system achieves structured, dynamic knowledge delivery, creates safe and efficient practical environments, and establishes multidimensional continuous improvement mechanisms. Practice demonstrates significant advantages in enhancing learning outcomes, engineering literacy, and innovation capabilities. The system provides a concrete pathway and reference model for engineering education digital transformation, with future work exploring deeper technology Integration and broader disciplinary application. The empirical case study and quantitative evaluation further validate the system's significant value in enhancing teaching quality and cultivating innovative talent. The success of this system underscores the transformative potential of AI in moving engineering education from a one-size-fits-all model to a personalized, experiential, and evidence-based paradigm. Future research will focus on longitudinal studies to track the long-term career impact on graduates and on developing standards for interoperability between different AI-powered educational tools to create a more open and flexible learning technology landscape.

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