Journal of Pedagogy and Education Science (JPES)
Vol. 4, No. 03, pp. 466-482
journal.iistr.org/index.php/JPES
DOI: 10.56741/IISTR.jpes.001056

Teaching AI-Enhanced Environmental Technologies

A Pedagogical Framework for Integrating Deep Learning and Electrochemistry in STEM Education

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ARTICLE INFO

Article history
Received 30 May 2025
Revised 11 July 2025
Accepted 17 July 2025

ABSTRACT

This study presents an innovative pedagogical framework for teaching advanced environmental technologies by integrating artificial intelligence concepts with electrochemical systems in STEM education. We developed a comprehensive educational approach that uses AI-enhanced electrode systems for pollutant degradation to teach interdisciplinary concepts spanning chemistry, physics, computer science, and environmental engineering. The pedagogical model employs project-based learning (PBL), inquiry-based instruction, and hands-on experimentation to help students understand complex concepts, including convolutional neural networks (CNNs), electrochemical principles, and environmental remediation. Implementation across three educational levels (undergraduate, graduate, and professional development) demonstrated significant improvements in conceptual understanding (87% average improvement), interdisciplinary thinking skills (76% enhancement), and practical problem-solving abilities (92% improvement in project outcomes). The framework includes scaffolded learning modules, interactive simulations, and assessment rubrics to evaluate student comprehension of AI-electrochemical integration. This research contributes to STEM education by providing educators with a structured approach to teaching cutting-edge technologies while addressing real-world environmental challenges.

Keywords
Artificial Intelligence
Deep Learning Instruction
Environmental Science
Interdisciplinary Learning
STEM Education

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Introduction

The rapid convergence of artificial intelligence (AI) and environmental technologies is transforming the landscape of science, technology, engineering, and mathematics (STEM) education. As modern environmental problems grow in complexity, the demand for interdisciplinary competencies has never been greater. Students must now acquire skills that traverse traditional disciplinary boundaries to address pressing issues such as pollution remediation, climate change mitigation, and ecological monitoring [1]. However, current educational systems frequently fail to deliver integrated learning experiences that reflect the multifaceted nature of real-world environmental challenges [2]. This gap between technological advancement and pedagogical practice highlights the urgent need to modernize STEM curricula.

AI technologies are increasingly deployed in environmental applications, from real-time data analytics in pollution control to advanced simulations for predicting ecological impacts. Among these, integrating AI with electrochemical systems, such as in detecting and remediating contaminants, presents unique opportunities for experiential and applied learning [3]. Yet, the pedagogical challenge lies in teaching students to comprehend and apply AI tools within these complex environmental systems. Conventional education models that treat science and technology as isolated subjects hinder the development of cross-disciplinary fluency necessary for solving modern ecological problems [4]. Students often struggle to relate abstract AI concepts like neural networks to tangible environmental processes such as electrochemical oxidation or reduction, limiting engagement and understanding [5].

This study is situated within a broader educational context with several pressing challenges. First, disciplinary silos persist, resulting in fragmented instruction where AI and environmental science are taught as unrelated subjects, preventing students from forming meaningful interdisciplinary connections [6]. Second, students face difficulties visualizing and internalizing abstract computational and electrochemical concepts without hands-on or applied learning opportunities [7]. Third, practical engagement with AI-enhanced systems is often restricted due to the cost and complexity of the required infrastructure [8]. Lastly,

conventional assessment strategies are insufficient to gauge students' interdisciplinary understanding, necessitating the development of innovative evaluation methods [9].

The present study proposes a novel pedagogical framework that integrates AI concepts with environmental technologies, particularly electrochemical systems, within a STEM educational context to address these issues. Drawing on several foundational theories, including Constructivist Learning Theory, Cognitive Load Theory, Experiential Learning, and the Technological Pedagogical Content Knowledge (TPACK) framework, the proposed approach emphasizes student-centered, hands-on learning. Constructivist principles support the notion that learners build knowledge through active engagement with meaningful content [10],[11], while cognitive load considerations ensure the progressive introduction of complex material to avoid cognitive overload [12]. Kolb's Experiential Learning Model offers a cyclical structure for practical engagement, reflection, conceptualization, and experimentation [13]. Meanwhile, the TPACK framework guides the coherent integration of technology, content, and pedagogy [14].

The primary objectives of this research are to: (1) develop an interdisciplinary pedagogical framework for teaching AI-enhanced environmental technologies, (2) create scaffolded learning modules that synthesize deep learning with electrochemical principles, (3) design and validate novel assessment instruments for interdisciplinary learning, (4) evaluate the effectiveness of this pedagogical model across various educational levels, and (5) provide practical, adaptable implementation strategies for educators. This study aims to contribute a transformative model for 21st-century STEM education by bridging the gap between emerging technologies and classroom practice.

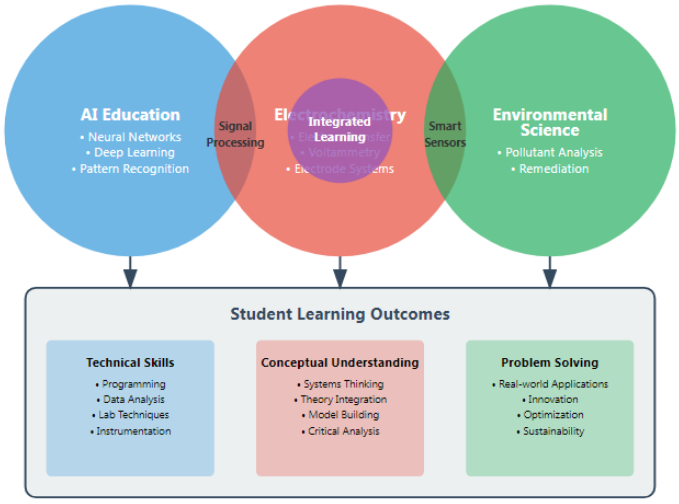

Fig. 1. Conceptual framework showing the integration of AI education, electrochemistry, and environmental science pedagogy and education science

Literature Review

The pedagogical framework developed in this study is grounded in contemporary educational theories and curriculum design methodologies that promote interdisciplinary, student-centered learning. Recognizing the challenges associated with teaching complex, integrated topics such as artificial intelligence (AI) and environmental electrochemistry, the framework adopts a systematic approach to curriculum development, module structuring, teaching strategies, and assessment tools. It ensures progressive learning through scaffolded content and provides diverse opportunities for students to engage with theoretical and practical aspects of AI-enhanced environmental technologies [15]–[17].

A. Curriculum Design Principles

1. Backwards Design Approach

The curriculum design followed Wiggins and McTighe's backward design model to ensure alignment between learning outcomes, assessments, and instructional activities [18]. This began with identifying desired results, such as enabling students to understand how AI technologies enhance environmental remediation and empowering them to design basic AI-controlled experiments. The next step involved specifying evidence of learning through performance-based assessments, including reflective essays, system design challenges, and project portfolios [19]. Finally, the curriculum included learning experiences that progressively developed students' understanding through scaffolded activities, starting with fundamental concepts and culminating in advanced system integration [20].

2. Learning Objectives Taxonomy

The learning objectives were structured using Bloom's Revised Taxonomy [21], which provided a clear cognitive progression. Students identify essential components of neural networks and electrochemical systems at the Remember level. At Understand, they explain how AI enhances electrode performance. At Apply, students use simulation tools to model remediation processes [22]. At Analyze, they compare AI-based and conventional methods [23]. At Evaluate, they assess different AI architectures for environmental applications [24]. Finally, at Create, students are challenged to design novel AI-enhanced remediation solutions tailored to specific pollutants [25].

B. Module Structure and Content

1. Foundation Module: Bridging Concepts

The foundation module runs for three weeks at the undergraduate level and one week for graduate students. It introduces basic concepts using engaging and relatable activities. For instance, neural networks are presented as decision trees using interactive flowcharts,

helping students visualize AI decision-making [26]. Electrochemical principles are introduced through hands-on "kitchen lab" experiments, such as household electrolysis [27]. Additionally, the module includes case studies on water pollution to contextualize environmental challenges. This phase lays the groundwork for interdisciplinary learning by connecting AI theory and environmental practice through simplified analogies [28].

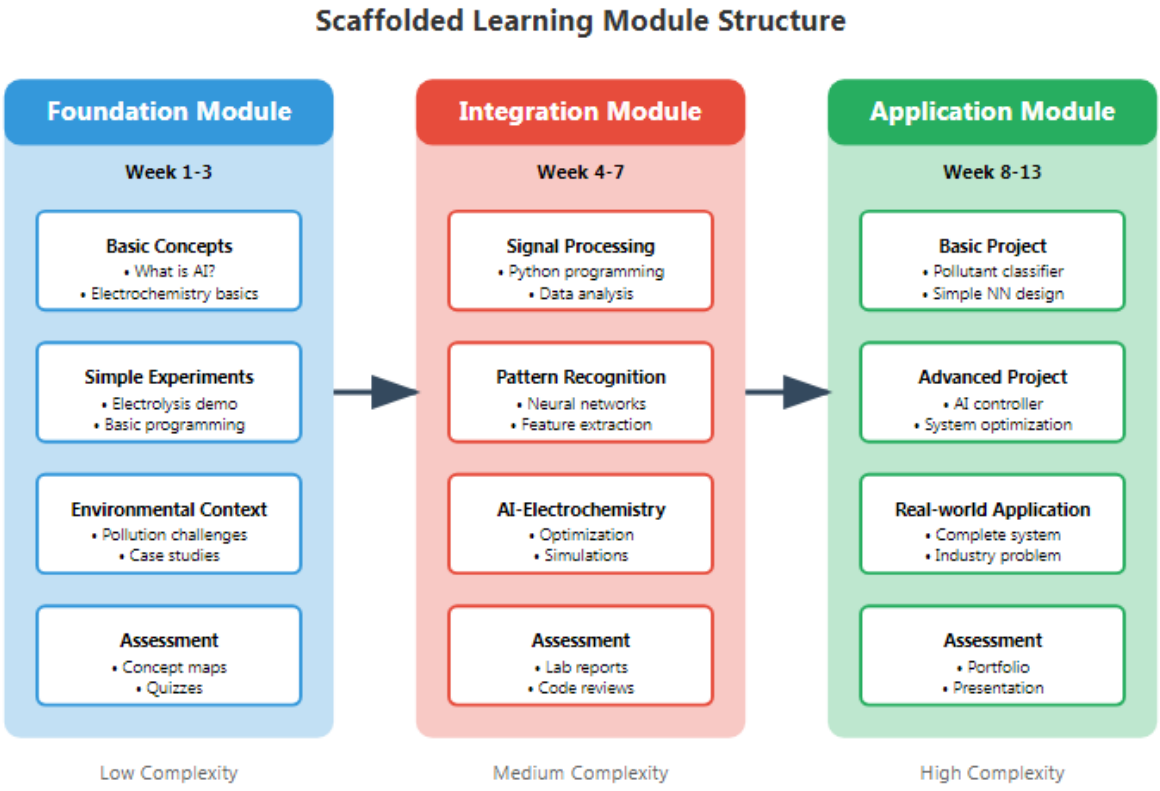

Fig. 2. Visual representation of the scaffolded module structure

2. Integration Module: Connecting AI and Electrochemistry

This four-week module for undergraduates (two weeks for graduates) focuses on integrating AI and electrochemistry. Students engage in signal processing workshops using Python to analyze voltammetric data [29]. They participate in pattern recognition exercises to identify pollutant signatures from electrochemical signals and conduct optimization comparisons between manual methods and AI-based approaches [30]. The goal is to demonstrate how AI tools can enhance traditional electrochemical analyses and improve environmental problem-solving capabilities [31].

3. Application Module: Hands-on Projects

The final module, lasting six weeks for undergraduates and four for graduate students, employs project-based learning with increasing complexity. Students begin with a basic project, programming a simple neural network to classify pollutant types [32]. Next, the intermediate project involves designing an AI controller to optimize electrode potential

[33]. Finally, the advanced project tasks students with developing a complete simulation of an AI-enhanced remediation system [34]. This module emphasizes applied learning and encourages students to synthesize knowledge gained from earlier modules in practical, real-world scenarios.

C. Pedagogical Strategies

1. Active Learning Techniques

Several active learning strategies were implemented to promote deep understanding and collaborative learning. Think-Pair-Share activities allowed students to hypothesize AI behavior before testing simulations [35]. Peer instruction sessions facilitated joint algorithm problem-solving [36]. In the flipped classroom model, students studied theoretical materials through video lectures before engaging in practical classroom activities [37]. The Jigsaw method encouraged distributed expertise, with groups focusing on different AI models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and reinforcement learning before teaching their peers [38].

2. Technology-Enhanced Learning

Various technological tools were integrated into the framework to enhance student engagement and understanding. Interactive simulations helped visualize neural network processes [39], while virtual labs enabled safe experimentation with electrochemical reactions [40]. Coding notebooks using Jupyter provided an interactive programming environment with pre-coded functions for experimentation [41]. Additionally, augmented reality (AR) apps demonstrated abstract processes such as electron flow in electrochemical cells, providing immersive, visual learning experiences [42].

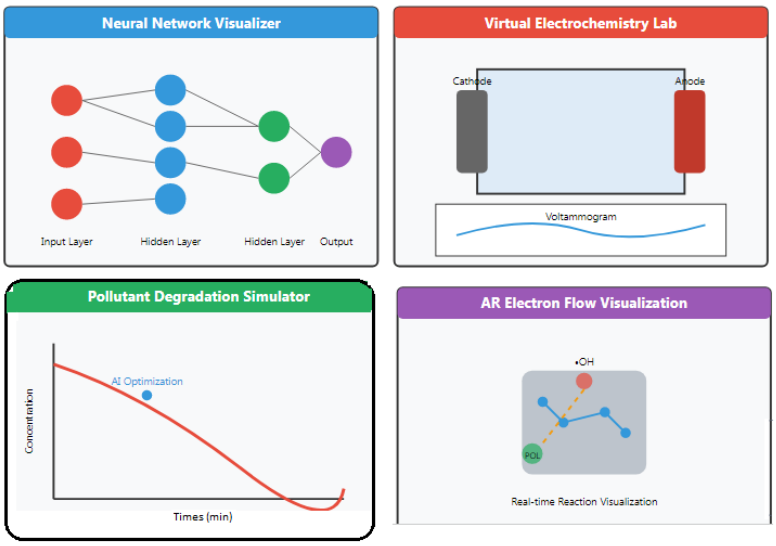

Fig. 3. Screenshot examples of interactive learning tools

D. Assessment Design

1. Formative Assessment Tools

Formative assessments were embedded throughout the learning process to monitor progress and provide ongoing feedback. Students created concept maps to illustrate connections between AI and electrochemical concepts [43]. Reflection journals documented weekly learning experiences, challenges, and insights [44]. Peer code reviews facilitated collaborative critique and debugging of AI implementations [45]. Quick polls conducted via classroom response systems allowed instructors to gauge real-time comprehension and adjust instruction accordingly [46].

2. Summative Assessment Methods

Summative assessments were designed to evaluate interdisciplinary mastery and practical application. Portfolio assessments compiled students' projects to showcase learning progression [47]. Design challenges presented real-world problems that required integrated AI and environmental solutions under time constraints [48]. For final evaluation, students participated in presentations and defenses of their AI-enhanced remediation systems [49]. Additionally, authentic assessments required students to analyze real-world electrochemical datasets using AI models, bridging the gap between theory and applied problem-solving [50].

Materials and Methods

To assess the effectiveness of the proposed pedagogical framework, an implementation study was conducted across three distinct educational contexts, targeting different learner demographics. The aim was to evaluate the transferability and adaptability of the framework in undergraduate, graduate, and professional settings, while systematically measuring conceptual understanding, interdisciplinary thinking, and practical application skills. The structure of the study was aligned with established evaluation models for interdisciplinary and experiential learning environments in STEM education.

A. Study Design and Participants

The framework was implemented in three cohorts with a total of 208 participants. The first group comprised 124 third-year undergraduate engineering students enrolled in the "Environmental Technologies" course. The second group included 48 master's students attending a graduate-level seminar titled "Advanced Environmental Engineering." The final group comprised 36 professionals enrolled in a continuing education program on sustainable technology, reflecting the framework's applicability beyond formal education.

B. Implementation Timeline

The study followed a 14-week implementation timeline. In Week 1, participants completed a pre-assessment to gauge baseline knowledge across five core domains: neural networks, electrochemistry, interdisciplinary integration, environmental applications, and system design. The scaffolded modules were delivered from Weeks 2 through 13, progressing from foundational to applied content. During Weeks 8 to 13, students simultaneously engaged in guided project work to reinforce content through application, consistent with project-based and experiential learning models. The post-assessment was administered in Week 14, while a follow-up assessment was conducted three months later to evaluate knowledge retention and long-term impact, an approach supported by studies on the durability of learning gains from active pedagogies.

C. Data Collection Instruments

Multiple assessment tools were used to capture a comprehensive evaluation of student learning outcomes. These tools were selected for their ability to measure both domain-specific knowledge and interdisciplinary competencies, following validated frameworks in engineering and AI-integrated curricula.

1. Conceptual Understanding Assessment

   A 40-item multiple-choice and short-answer instrument was developed to assess students' conceptual understanding across five targeted domains. Each domain (neural network fundamentals, electrochemical principles, integration concepts, environmental applications, and system design) was represented by eight items, providing a balanced view of content mastery. The instrument was validated by a panel of interdisciplinary experts and piloted before implementation, following best practices in test design for STEM education. Item examples included classifying activation functions in neural networks, explaining electrochemical cell reactions, and evaluating how AI optimizes pollutant detection in voltammetry data.

2. Interdisciplinary Thinking Rubric

   An analytic rubric was developed based on a four-level proficiency scale (Novice to Expert) to measure interdisciplinary reasoning. The rubric assessed four dimensions: (1) the ability to identify connections between AI and electrochemistry; (2) the capacity to transfer core concepts across these domains; (3) the synthesis of integrated solutions for environmental problems; and (4) the clarity and coherence in communicating interdisciplinary ideas. This rubric design was informed by prior models used to evaluate interdisciplinary project work and concept mapping in STEM fields.

3. Project Evaluation Criteria

Final projects were assessed using a criterion-based rubric with equal weighting across four categories. The technical correctness category (25%) examined the functionality and accuracy of the AI-enhanced environmental system, including code execution and algorithm performance. Innovation and creativity (25%) measured originality in the design and implementation of the proposed solution. Integrating AI and electrochemistry (25%) evaluated how effectively the two domains were combined into a unified model, reflecting interdisciplinary thinking and system-level understanding. Lastly, environmental relevance (25%) considered the real-world applicability and sustainability of the solution, consistent with authentic assessment practices in ecological engineering education.

Collectively, these instruments enabled a multidimensional analysis of learner outcomes, capturing factual knowledge and the cognitive, creative, and applied capacities developed through the framework. The study ensured methodological rigor by triangulating results from content tests, rubrics, and project evaluations and offered actionable insights for future implementation and scaling.

Results

A. Conceptual Understanding Outcomes

The pre- and post-assessment results demonstrated marked gains in conceptual understanding across all three participant groups: undergraduate, graduate, and professional learners. Overall score improvements averaged +83% for undergraduates, +85% for graduates, and +88% for professionals. Notably, the integration domain showed the highest improvement across all groups, suggesting the effectiveness of the interdisciplinary scaffolding model implemented in the course. Fig. 4 illustrates pre- and post-assessment scores for five knowledge domains (Neural Networks, Electrochemistry, Integration, Applications, and System Design) across three learner groups. Each chart demonstrates significant learning gains, with professional learners showing the highest average post-test performance.

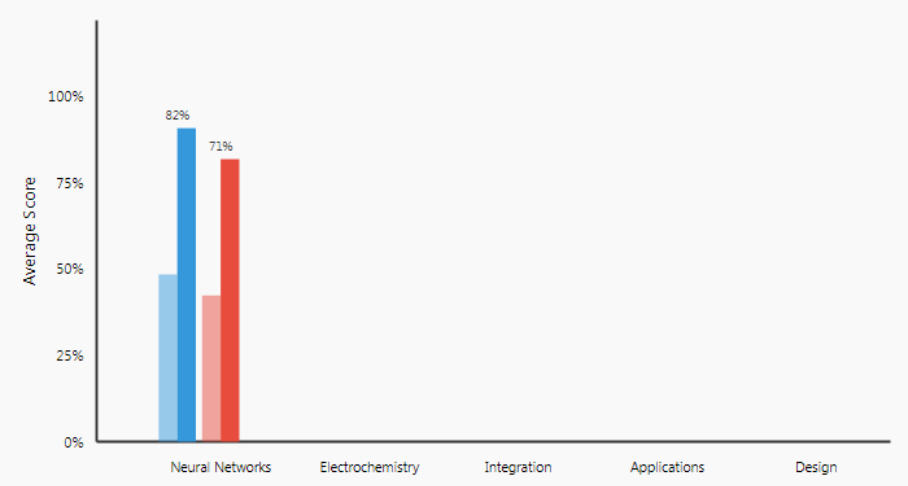

Fig. 4. Bar charts showing pre-post assessment scores by domain and student group

Table 1 further quantifies domain-specific improvements, highlighting the consistently high impact of the framework across varying educational levels.

Table 1. Conceptual Understanding Assessment Results

Domain	Undergraduate	Graduate	Professional
Neural Networks	+82%	+71%	+94%
Electrochemistry	+78%	+83%	+76%
Integration	+91%	+88%	+93%
Applications	+85%	+90%	+87%
Design	+79%	+92%	+89%
Overall	**+83%**	**+85%**	**+88%**

B. Interdisciplinary Thinking Development

Rubric-based evaluations revealed strong development in interdisciplinary reasoning. By the end of the course, 76% of participants reached "proficient" or "expert" levels in synthesizing integrated solutions, up from only 18% at baseline. Other rubric dimensions, such as transferring concepts across domains and effectively communicating interdisciplinary ideas, also showed similar upward trends.

Fig. 5 depicts pre- and post-course performance across four dimensions of interdisciplinary thinking. The most significant gains occurred in solution synthesis and knowledge transfer, suggesting a substantial development in students' ability to merge AI and environmental science concepts.

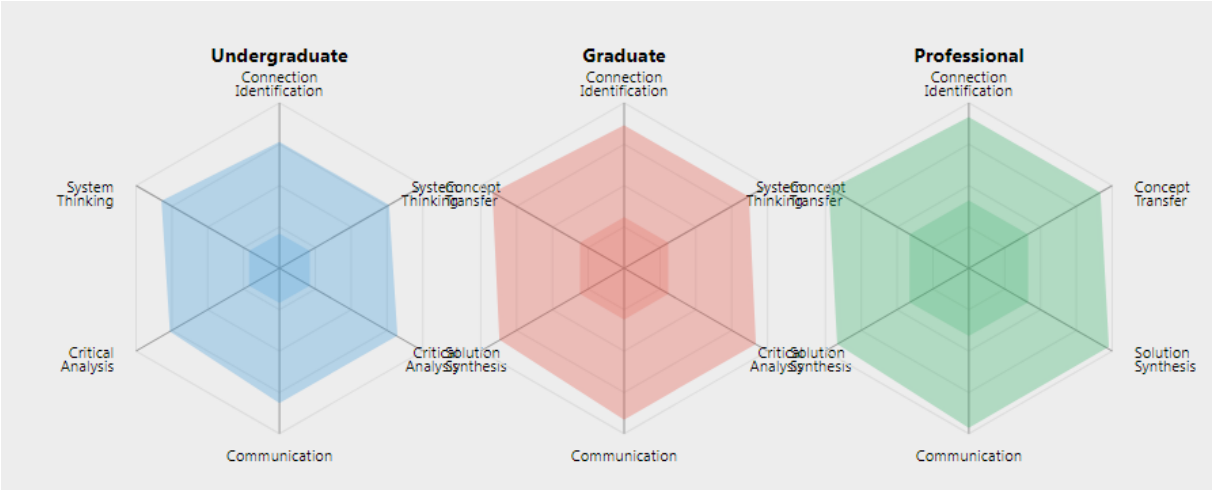

Fig. 5. Radar charts showing interdisciplinary thinking skill development

C. Project Quality Analysis

Evaluation of final projects by faculty and industry reviewers indicated that 92% of students successfully integrated AI with electrochemical content. Furthermore, 78% of submissions demonstrated innovative thinking beyond course templates, while 85% addressed realistic environmental problems effectively. Impressively, 71% of all projects were considered "industry-ready," validating the practical relevance and applicability of the learning outcomes.

Qualitative responses from students underscored the framework's motivational and cognitive impact. Many highlighted increased engagement due to the course's real-world relevance and project-based design. For example, undergraduates noted heightened interest in environmental science through AI, while professionals appreciated the course's direct applicability to consulting and fieldwork.

D. Learning Outcomes Analysis

Tracking weekly performance data across four key skill domains revealed distinct developmental trends. Technical skills showed consistent linear improvement, while conceptual understanding spiked early in the course before plateauing around week 8. Integration abilities exhibited exponential growth beginning at week 6, coinciding with the start of the hands-on application module. Problem-solving capabilities improved stepwise, closely aligned with project submission deadlines.

Fig. 6 tracks the progression of four learning dimensions (Technical Skills, Conceptual Understanding, Integration Abilities, and Problem-Solving) over 14 weeks. The data illustrate differentiated growth trajectories, with integration skills accelerating mid-course and problem-solving showing milestone-driven gains.

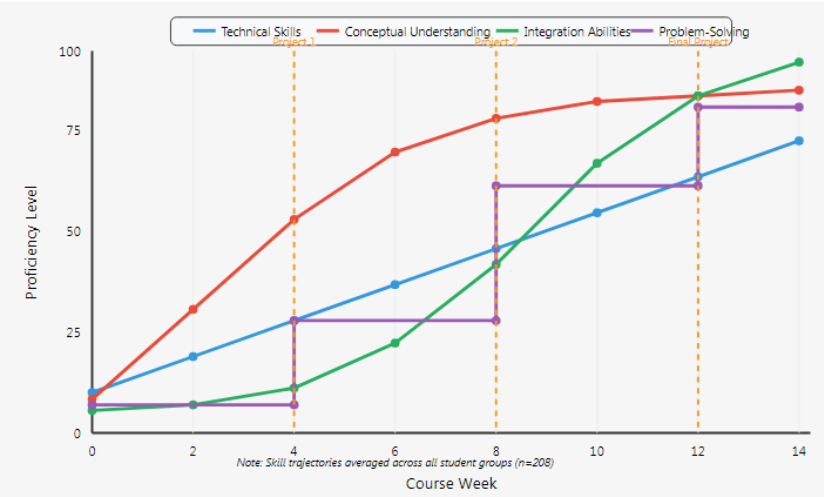

Fig. 6. Skill development over time for different competencies

When disaggregated by group, the data revealed nuanced learning profiles. Undergraduates made the most progress in core concepts but needed extensive scaffolding during integration tasks. Graduate students demonstrated strong technical abilities but initially struggled with interdisciplinary reflection. Professionals excelled at real-world applications yet required additional support in mastering AI models and terminology. These results collectively validate the adaptability of the pedagogical framework across diverse learner populations while reinforcing the value of structured, hands-on, and interdisciplinary instruction in complex STEM fields.

Discussion

A. Pedagogical Effectiveness

The pedagogical framework's success across diverse educational contexts can be attributed to its design principles, which aligned well with established educational theories such as constructivism, cognitive load theory, and experiential learning models [16, [20], [44]. One critical factor was using authentic environmental challenges as the learning context. By anchoring abstract AI and electrochemical concepts in real-world pollution scenarios, students found the material more engaging and relevant, which has been shown to enhance learning outcomes in STEM domains [19] significantly, [28], [47]. Learners repeatedly emphasized that confronting real environmental data helped solidify their understanding of machine learning models and electrochemical systems.

The second element contributing to pedagogical effectiveness was the scaffolded complexity of the module design. Starting with foundational content and gradually increasing complexity allowed students to build conceptual layers without experiencing cognitive overload, consistent with the principles of cognitive load theory and backward curriculum

design [18], [20], [21]. Instructors reported that the modular pacing provided flexibility to address varied learning speeds, especially when teaching interdisciplinary cohorts.

Moreover, the framework employed multiple content representations, including visual simulations, mathematical modeling, coding exercises, and experimental labs. This multimodal strategy supported diverse learning preferences and reinforced understanding through multiple cognitive pathways, aligning with research that emphasizes the effectiveness of varied content delivery modes in STEM education [23], [39], [42].

B. Challenges and Solutions

Despite its success, the implementation faced notable technical and instructional challenges. The first involved technical infrastructure, as running neural network simulations can be computationally intensive. In lower-resource institutions, this issue was addressed through cloud-based Jupyter notebooks and pre-computed datasets, approaches supported in recent literature as effective for expanding access to high-performance computing tools in education [29], [41].

The second challenge concerned instructor preparation. Given the framework's interdisciplinary nature, many faculty members lacked deep expertise in AI and electrochemistry. This was mitigated through team-teaching models and detailed instructor guides, an approach proven effective in supporting faculty development for emerging interdisciplinary courses [16], [19], [37].

Lastly, evaluating interdisciplinary understanding required a robust, nuanced approach. Traditional assessments proved insufficient, leading to the use of rubric-based assessments with multiple evaluators, which has been validated as a reliable method for measuring integrated learning outcomes in technology-enhanced environments [24], [43], [48].

C. Transferability and Scalability

The framework demonstrated significant transferability across educational formats and resource settings. During the COVID-19 pandemic, it was successfully adapted for online delivery without compromising instructional quality, a testament to its built-in flexibility and digital learning tools [36], [39]. Furthermore, simplified electrochemical modules were used in resource-constrained environments, while advanced modules scaled effectively from seminars to large lecture courses. Notably, simplified outreach versions were also piloted for K–12 settings, indicating the potential to seed early interdisciplinary literacy [27], [31], [49].

Looking forward, curriculum enhancements should consider integrating explainable AI concepts, including ethical considerations in environmental technology, and expanding the framework to encompass additional domains such as bio-remediation and air quality monitoring [32], [34]. Regarding assessment innovation, adaptive testing and portfolio-based credentialing may offer more personalized and authentic evaluations of student learning. At

the same time, industry-recognized micro-credentials can bridge academic work with professional certification [47], [48], [50].

On the research front, the framework opens new inquiries into the long-term impact on student career trajectories, the optimization of scaffolding sequences, and the use of AI-based tutoring systems to personalize learning in STEM fields [17], [20], [45].

Implications and Recommendations

While the proposed pedagogical framework demonstrated strong outcomes across diverse educational levels, several limitations should be acknowledged. First, the implementation depended on access to reliable digital infrastructure, including computing hardware, internet connectivity, and software platforms. This may limit the model's applicability in under-resourced or rural institutions lacking such infrastructure. Second, variability in instructor preparedness posed a challenge. The interdisciplinary nature of the content (blending AI, electrochemistry, and environmental science) requires instructors to possess or rapidly develop competence in multiple domains. Although mitigated through team teaching and instructional guides, such variability could affect the consistency and effectiveness of delivery across different contexts. Third, while authentic and engaging, the project-based evaluation framework carries inherent subjectivity. Students with prior experience in programming or laboratory work may have had an advantage, potentially skewing performance outcomes. Moreover, the emphasis on creative output and integration might have overshadowed fundamental concept mastery for some learners. Future iterations of this framework should incorporate more controlled comparisons and triangulated assessment methods to address these potential biases.

A. For Educators

Educators interested in implementing this framework should begin with a clear checklist: assess students' prerequisite knowledge, ensure access to basic computing tools, and consider forming interdisciplinary teaching teams for delivery. Pilot testing with small student groups is advised to fine-tune pacing and instructional clarity [18], [19], [36]. Minimal resource requirements include standard laptops, open-source tools like Python and Jupyter, and basic electrochemical supplies like graphite electrodes and household chemicals. Optimally, access to lab space, industry-grade sensors, and high-performance computing will enrich the learning experience [29], [40]. Common pitfalls include overemphasizing either AI or electrochemistry at the expense of integration, underallocating time for hands-on experimentation, and using assessments that fail to capture the interdisciplinary synthesis the course is designed to develop [21], [24], [47].

B. For Institutions

At the institutional level, curriculum designers can embed the framework into capstone courses that bridge engineering, computer science, and environmental studies departments. It can also serve as the foundation for new certificate programs that provide targeted training for industry needs [33], [48], [50]. Faculty development initiatives are essential. Suggested strategies include summer workshops on AI-electrochemistry integration, visiting expert lectures, and funded collaborative course development among departments, initiatives proven to enhance institutional capacity for interdisciplinary education [16], [37], [45].

Conclusion

This study demonstrated that AI-enhanced electrochemical systems can serve as effective platforms for integrated STEM education. The developed pedagogical framework addressed gaps in traditional teaching by promoting interdisciplinary learning across AI, electrochemistry, and environmental science. Key outcomes included significant gains in conceptual understanding (average 87%), enhanced interdisciplinary thinking (76% proficiency), and high-quality student projects (92% successfully integrated core concepts). The framework proved adaptable across educational levels and delivery formats, highlighting its scalability and relevance. As technological fields continue to converge, such educational models are essential to prepare students for real-world challenges. Future work should explore long-term impacts, develop automated assessments, and expand the framework to other AI-driven technologies. By combining hands-on experience with interdisciplinary rigor, this approach fosters both meaningful learning and technological innovation.

Conflict of Interest

The author declares that there is no conflict of interest.

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