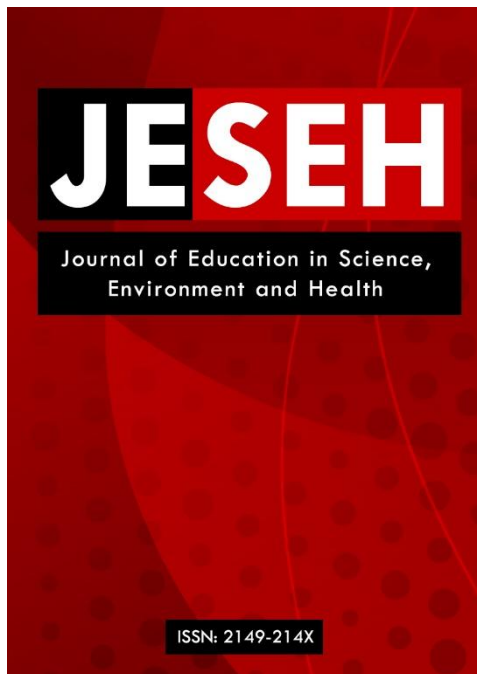




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Pedagogical Applications of Artificial Intelligence for Environmental Disciplines: A Systematic Review for Higher Education

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Abstract

The integration of artificial intelligence (AI) with teaching activities has become a hotspot in education, offering transformative potential for improving learning outcomes. This review aims to examine the pedagogical integration of AI within environmental disciplines for higher education, analyzing its practical scenarios, merits and drawbacks. Literature was retrieved from Web of Science and Scopus, with 10 qualified studies selected covering environmental science and engineering disciplines. Building upon this synthesis, supplemented with analogous cases from related disciplines (e.g., basic chemistry and engineering courses) that are also transferable to environmental education, the expanded discussion identified typical AI applications covering virtual assistants, adaptive learning, virtual experiments and intelligent evaluation. Though limited by insufficient empirical data and publication bias, findings suggest that AI holds transformative potential for environmental education, especially in enhancing personalized learning experiences, boosting teaching efficiency, increasing student engagement, and enabling data-driven instructional decision-making. However, limitations such as insufficient data quality, ethical and academic integrity concerns, uneven technical accessibility, and lack of long-term empirical validation were also consistently reported. More rigorous, longitudinal, and discipline-specific research is required to validate the observed benefits. Corresponding suggestions are put forward to better balance generic technological advancement and deep integration with discipline-specific teaching practice.

Introduction

Global environmental challenges are interconnected rather than isolated. This systemic nature demands integrated, cross-disciplinary solutions, rather than over-reliance on a single technology or policy intervention. For instance, fossil fuel consumption not only exacerbates greenhouse gas emissions but also contributes simultaneously to air pollution and ocean acidification (Zandi Lak et al., 2024). Accordingly, innovative talents in the environmental sector are expected to demonstrate interdisciplinary integration capabilities, practical innovation competence, and a global vision. Against the backdrop of rising global demand for high-quality applied and innovative professionals (Brown et al., 2021), practice-oriented higher education has gained increasingly prominent strategic significance. This has driven governments and universities to establish policy frameworks aimed at strengthening experiential learning and fostering students' practical skills, innovative thinking, and social adaptability (de Carvalho Silva et al., 2026). Nevertheless, traditional teaching approaches suffer from notable limitations. Standardized curricula and passive learning modes fail to satisfy students' individualized learning needs, while the integration of theory and practice remains inadequate (Sajja et al., 2025). Furthermore, conventional education struggles to accommodate the requirements of multidisciplinary integration and dynamic data interaction inherent in complex disciplines such as environmental science (Sajja et al., 2025).

Artificial Intelligence (AI) is an emerging technological field dedicated to developing theories, methodologies, technologies, and application systems that simulate, extend, and augment. In contemporary society, AI is fundamentally reshaping human lifestyles. The education sector is also experiencing a paradigm shift driven by the adoption of AI. Amid the accelerated digital transformation of education spurred by the unexpected pandemic of the COVID-19, the rise of generative AI has introduced additional challenges and opportunities to this field (Yuriev et al., 2024). Current exploration of AI in education covers personalized learning, automated assessment, and intelligent tutoring systems (AlAfnan et al., 2023). In the present context, students can use generative AI to retrieve information, draft essays, or refine their assignments (Hamamra et al., 2024). Teachers can also utilize AI tools to gain deeper insights into students' learning processes and tailor learning experiences to individual needs (AlAfnan et al., 2023). Furthermore, intelligent tutoring systems (Bardach et al., 2026) and automated grading functions (AlAfnan et al., 2023) can offer supplementary support beyond formal classroom settings, thereby

alleviating teachers' administrative workload (Williamson et al., 2020). In addition, the development of practical competencies typically relies on training in real-world contexts, which has long been restricted by the uneven distribution of educational resources across schools and society, leaving remote and underprivileged areas particularly underserved. The integration of AI to simulate practical scenarios would help alleviate this disparity and promote more equitable access to educational resources (Liang et al., 2025).

In parallel with technological advancements, higher education pedagogy is constantly evolving to better foster students' practical competencies and problem-solving capabilities. Contemporary instructional approaches, such as problem-based learning (PBL) (Liu & Pasztor, 2022), outcome-based education (OBE) (Tang et al., 2026), and the university-industry collaboration (Zhuang & Zhou, 2023), have emerged as responses to the demands of the new era. These approaches emphasize the active construction of knowledge, engagement in authentic tasks, and the bridging of classroom learning with real-world practice. The integration of AI tools further amplifies the implementation of these pedagogical innovations. AI can provide dynamic scaffolding for problem-solving activities, generate authentic, context-rich scenarios for production-oriented tasks, and facilitate data-informed alignment between academic curricula and industry needs.

Moreover, the use of AI not only facilitates the practice of new teaching thinking but also deepens classic educational theories. Constructivist learning theory posits that learners actively construct knowledge through interaction with their environment; as a cognitive tool, AI can support the principles of constructivism by enabling simulation-based, inquiry-driven learning experiences (Yan et al., 2025). Mayer's cognitive theory of multimedia learning could offer the critical design principles for AI-generated visualizations and explanations, helping to manage cognitive load and enhance knowledge comprehension (Hamizi & Mokmin, 2026). While the technological pedagogical content knowledge (TPACK) framework emphasizes that effective technology integration requires not only technical proficiency but also a profound synergy among technology, pedagogy, and domain-specific content, the development of AI tools for teaching and learning must be aligned with the core requirements of educational theories and teaching practice, rather than being purely technology-driven (Feldman-Maggor et al., 2025; Wang et al., 2024).

The intersection of AI and education has emerged as a fertile ground for review studies. Recent comprehensive review has synthesized the landscape of AI applications in general K-12 education, identifying common tools and learning outcomes (Yue et al., 2022), while another review focused on the integration of AI with learning management systems (LMS) or extended reality (XR) in higher education, documenting benefits such as personalized learning and adaptive assessment, alongside challenges including data privacy concerns and algorithmic bias (Alotaibi, 2024; Lázaro & Duarte, 2023). Beyond these, additional reviews delved into AI's implications for specific populations and themes, such as the professional identity of English as a Foreign Language (EFL) pre-service teachers (Zhu et al., 2025), environmental health teaching (Ross et al., 2023) and anatomy education (Abdellatif et al., 2022). Notably, despite this growing body of review work, a critical gap remains: there is no dedicated, systematic review focusing on the intersection of AI and environmental disciplines pedagogy. Environmental science teaching in higher education is distinct from environmental education at the K-12 level or the simple awareness of sustainability concepts often emphasized in general education. Rather, it constitutes an interdisciplinary, application-oriented professional discipline that places high demands on students' knowledge breadth, comprehensive competencies, innovative thinking, and practical skills. Given these inherent pedagogical challenges, the complexity of the subject matter and the need to integrate multiple knowledge domains with real-world problem-solving, there is a clear imperative to actively adopt both emerging pedagogical innovations and advanced technological tools. This recognition serves as the starting point and foundation rationale for the present review.

AI has been successfully deployed in environmental science research. For instance, it has been utilized as a highly effective approach for the on-site calibration of air quality multi-sensors systems (De Vito et al., 2020) and for the real-time monitoring and prediction of water quality parameters and algae concentrations (Saboe et al., 2021). However, its targeted application in environmental science teaching remains nascent and fragmented. Although the existing educational literature highlights the potential in personalization and simulation in teaching, it largely consists of conceptual proposals rather than empirical or practical implementations. Consequently, a significant research-practice gap persists. The key research gaps this review addresses are: (1) the lack of a synthesized overview of how AI specifically caters to the pedagogical demands of environmental science education; (2) insufficient analysis of the effectiveness and limitations of AI application in this teaching context; and (3) the absence of an actionable framework for educators to navigate the challenges and opportunities associated with AI integration in this field.

To fill these gaps, this review endeavors to collect relevant papers and cases, aiming to systematically identify, analyze, and synthesize the emerging applications of AI in environmental science education, and to propose a theoretically grounded agenda for future research and practice. This review would be the first systematic review to specifically target AI's pedagogical role within environmental disciplines for higher education, differentiating it from broader reviews. Moreover, this study would serve as a crucial bridge between the rapid technological advancements in AI and the enduring pedagogical needs of environmental science educators, thereby advancing equitable and effective integration of AI in this critical field.

Method

Information Sources and Inclusion Criteria

The present literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) protocol (Page et al., 2021), which provides a methodological framework for the search, selection and analysis of the existing scientific literature. The databases selected for this review included Web of Science (WoS) and Scopus (1999-present). Based on our proposed aim, we considered the literatures from the field of the environmental disciplines that reported the applications of AI-empowered tools in teaching activities. An inclusion criterion was applied that the paper must be a research article or conference paper written in English. Book chapters could be included if they reported practical cases.

Search Strategy and Selection Process

The search strategy corresponding to our study topic involved three main keyword groups: artificial intelligent, teaching, and environmental disciplines. The search was first carried out in the WoS database. We combined these keywords using Boolean operators to form the following research query: (“artificial intelligence” OR “AI”) (Topic) AND (“Teaching” OR “pedagogical applications”) (Topic) AND (“Environmental Sciences” OR “Engineering, Environmental” OR “Environmental Studies” OR “Environmental Sciences & Ecology”) (Web of Science Categories). The last search was carried out on 23rd March, 2026. Limited to the “Web of Science Core Collection”, it yielded an initial 148 documents.

A similar search was conducted in the Scopus database. Since Scopus does not use the same category system, the research query was modified as follows: (“artificial intelligence” OR “AI”) (Article title, Abstract, Keywords) AND (“Teaching” OR “pedagogical applications”) (Article title, Abstract, Keywords) AND (“Environmental Sciences” OR “Environmental Engineering” OR “Environmental Studies” OR “Ecology”) (Article title, Abstract, Keywords). This search, last conducted on 23 March 2026, initially yielded 162 documents.

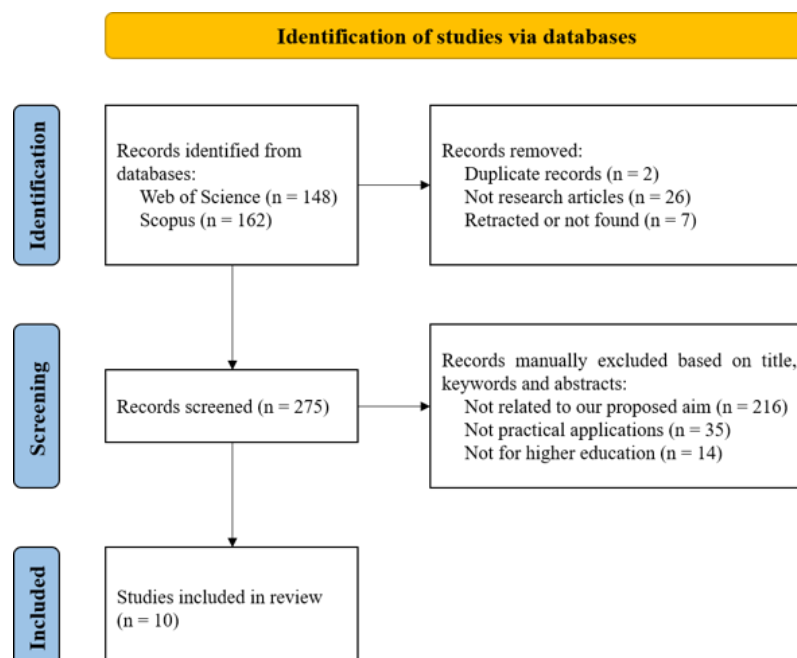


Figure 1. Identification of studies via databases. Source: Produced by the authors from (Page et al., 2021)

Screening

After removing the duplicate records and filtering out review articles and retracted paper, a total of 275 articles were then screened. The title, abstracts and keywords of these articles were carefully examined. Due to semantic ambiguity, keywords such as “educational ecology” and “learning environment” were inadvertently included. We therefore manually excluded records that (1) were not related to our proposed aim; (2) did not report practical applications; or (3) were not applied to higher education. These exclusion criteria reduced the number of articles from 275 to 10. The PRISMA 2020 flow diagram for the present systematic reviews was displayed in Figure 1. To support an in-depth discussion, additional cases from other relevant disciplines (e.g. chemistry, ecology, material science or engineering) or other grades (e.g. primary and secondary schools, K-12 or STEM education), which had been excluded during the screening, were partially included to allow extended comparison and analysis.

Data Extraction

The resulting 10 articles were then summarized in the results. The main information including the location of the reported case, the related course, the AI tools employed, the improvements in teaching and learning, as well as the limitations identified at the time, were extracted from the articles where applicable. These data were then tabulated and narratively synthesized.

Results and Discussion

Summary of the Extracted Data

Table 1 summarizes the 10 case studies on AI applications in environmental disciplines, spanning three geographic regions: China (n=6), the United States (n=3), and the Philippines (n=2). The studies cover a range of environmental and civil engineering curricula, including general environmental science, environmental engineering, conservation ecology, and natural resources education. A diverse set of AI tools was deployed, including AI-enhanced simulation/virtual reality (VR) platforms, machine learning for data processing, generative AI (e.g., GPT) integrated with LMS, and specialized AI analysis modules. Across all contexts, AI integration consistently demonstrated positive outcomes, including enhanced student engagement and learning performance, improved critical thinking and problem-solving skills, increased efficiency in data-intensive tasks, and personalized learning pathways. However, several shared challenges were identified: methodological limitations (e.g., lack of longitudinal empirical validation), technical resource barriers, low engagement with structured AI features, ethical risks of over-reliance on AI, and gaps in pedagogical guidance and discipline-specific content alignment. These findings highlight both the transformative potential of AI in environmental education and the critical need for targeted solutions to address implementation barriers.

Table 1. Summary of AI applications in environmental disciplines/courses

Country	Discipline /Course	AI Tool	Effectiveness	Challenges	Source
China	Dual-qualified teacher training for AI+ environment	AI-enhanced simulation experiment	Enhanced innovation skills; Synergistic effects from multi-dimensional collaboration	Lack of empirical validation with longitudinal cohort data; Student learning outcomes not modeled endogenously; Generalizability limited by aggregate national statistics	(Liu et al., 2025)
China	Environmental science	Machine learning for visualization experiments	Automated batch processing; Low cost; supports student-led experiments; Improved accuracy and efficiency	Initial setup requires basic training in ImageJ and scripting	(Wang et al., 2025)

China	Environmental engineering	AI-controlling VR teaching platform	Improve student engagement, technical proficiency, and understanding of control principles.	requires MATLAB/Simulink and VR setup	(Li et al., 2025)
China	Green shipping monitoring (Air pollutant emissions)	AI-enhanced VR simulated experiment	Better learning performance; Better participation; Active performance inspired by individual thinking.	Necessary to expand the size and dimensionality of data	(Zhao et al., 2023)
China	Habitat Conservation	An AI-environmental system analysis module	Improved scenario simulation; Initializing systemic thinking and responsible AI literacy	Weak foundational knowledge; Risks of “technological dependency” and “critical thinking deficits”	(Lin et al., 2026)
United States	Environmental / Civil Engineering	AI video generation platform	Improved production efficiency; Higher student engagement; Low barrier for engineering educators	No significant promotion in learning effectiveness; Still requires human review; Lack of discipline-specific focus	(Christina et al., 2025)
United States	Civil and environmental engineering	Analyzing a large air quality dataset by using GenAI	Students valued AI for troubleshooting, advice, and brainstorming	Lack of structured guidance	(Matthew Yukio et al., 2025)
United States	Civil and environmental engineering	GPT integrated with LMS	High convenience and comfort; helpful for homework and concept understanding; strong student interest	Ethical uncertainty; Low engagement with structured features; Conversational memory issues	(Sajja et al., 2026)
Philippines	Environmental education	AI-powered simulations; Real-world data analysis tools	Personalized learning pathways; Enhanced student engagement; Immersive experiences; Critical thinking and problem-solving	Declining collaboration; Less exposure to fieldwork; Over-reliance on AI; Oversimplification of complex ecosystems	(Calzada et al., 2025)
Philippines	Natural resources and environmental science	GPT-assisted collaborative research	Enhanced student engagement; Improved critical thinking and problem-solving skills	Risk of over-reliance on AI; Potential bypass of reflective processes; Need for human verification and contextualization	(Santiago, 2025)

Study Risk of Bias Assessment and Quality Assessment

To minimize potential bias, the study design, as well as the entire process of literature retrieval and screening for analysis, was implemented collaboratively, systematically, and rigorously. For the study design, the authors, all frontline educators in the field of environmental science and engineering, jointly formulated the analytical objectives and literature retrieval criteria. An initial round of screening was completed independently by one researcher, after which all team members collectively reviewed and discussed the results. In addition, the research team successfully obtained full texts for all included published studies, enabling in-depth analysis and significantly mitigating bias that could otherwise result from limited access to complete articles.

The two databases employed in this PRISMA-based systematic review, WoS and Scopus, aggregated the most influential research outputs worldwide. However, it must be noted that the knowledge contained in these databases was not entirely neutral or objective. On the one hand, the vast majority of the included outputs were journal articles, while books and other publication types more commonly found in the field of education accounted for a relatively low proportion. On the other hand, the literature was predominantly written in English, leading to an overrepresentation of perspectives from English-speaking countries. Furthermore, and particularly importantly, educational cases were rarely developed into case-based papers; as most educators might tend to focus either on theoretical analysis or on classroom teaching practices. Consequently, this review inevitably encountered certain difficulties in capturing and synthesizing rich, context-dependent pedagogical cases.

Nevertheless, based on a systematic analysis of the finally selected literature, combined with the shared experience of relevant disciplines and the authors' own teaching practice, this study identified common application scenarios of AI tools in higher education related to environmental science, and summarizes current limitations as well as key directions requiring further breakthroughs in future research and practice. These analytical results, together with the ensuing discussions and recommendations, would provide relevant educators with clear pathways for continuously improving AI applications and deepening the integration of AI tools into teaching. In summary, this review confirmed that all the articles analyzed meet the quality criteria required to address the research objectives of this study.

Drawing on the 10 core case studies above and supplemented with other relevant disciplinary course examples, the following discussion explores four pivotal dimensions of AI integration in educational settings: applicable teaching scenarios, primary pedagogical benefits, prevailing implementation challenges, and prospective future directions. This analysis aimed to present a comprehensive overview of AI in education, and, more critically, to offer context-specific, actionable recommendations for the strategic integration of AI tools in environment-related courses.

Typical Pedagogical Applications of AI for Environmental Disciplines

Teaching Assistance

As versatile pedagogical aids, AI chatbots support students by explaining concepts and answering questions in real-time. This immediate feedback loop improves learning outcomes and extends educational engagement beyond formal instruction. For instance, in foundational environmental science courses such as basic chemistry (Alasadi & Baiz, 2024), leveraging the image input functionality of models such as GPT-4 could assist students in interpreting chemical diagrams, molecular structures, and spectroscopic data. Moreover, these systems could recognize handwritten calculations and tabular data, thereby offering interactive tutoring support. Utilizing in this way, AI can help mitigate cognitive decline and sustain learning efficacy. Additionally, AI-generated content was often more comprehensible and engaging than traditional research websites, aligning with and stimulating students' curiosity (Nayyar et al., 2025). Research has systematically integrated generative AI into the pre-class phase of a Chemical Process Control course (Huang, 2026). Through structured resources such as annotated handouts, instructional videos, and interactive AI sessions, students were guided to grasp complex concepts in advance and engage in programming exercises, thereby establishing a foundation for deeper in-class learning. Chang and colleagues (Chang et al., 2018) proposed an intelligent learning support system that employ General Rapid Annotation Clustering Enhancement to help teachers create and manage students' online reading activities, as well as assist students in exam preparation. GPT has also proven effective in both teaching assistance and learning support (Sajja et al., 2026; Santiago, 2025). Additional applications may include tasks such as formulating instructional plans, generating questions for written exams and practical evaluations, as well as explaining concepts while addressing student inquiries (Modran et al., 2024). Similarly, the AI teaching assistant system on the Chaoxing Fanya platform has demonstrated comparable effectiveness in these areas (Wu et al., 2025).

Personalized Learning

Adaptive learning technologies are transforming education by customizing educational content to individual learners' needs, capabilities, and interests, thereby enhancing learning efficiency and engagement (Sajja et al., 2025). Besides of the summarized cases in Table 1 (Calzada et al., 2025), another example is the Educational AI Hub system, which was tailored to the diverse needs of both students and instructors. It provided personalized learning pathways, advanced content support, prioritizes accessibility, and fostered an inclusive and secure learning environment. In particular, regarding adaptive learning, it was capable of recognizing users' emotional states and adjusting its responses accordingly (Sajja et al., 2025). While the COVID-19 pandemic led to a surge in distance education, effective learning for many students has been hindered by a lack of intrinsic motivation to acquire new knowledge and develop professional skills remotely. This situation highlights the growing necessity for personalized adaptive learning. At the same time, participants in contemporary training programs increasingly expect customized course offerings that accurately match their personal requirements, ability profiles, and learning aptitudes.

AI-based knowledge graphs can typically be used to track learning progress and provide personalized learning guidance. The efficacy of generative AI and large language models (LLMs) in constructing and completing educational knowledge graphs has been examined (Jhajj et al., 2024). By leveraging the multi-model database and visualization framework, a visualized system for a curriculum Knowledge Graph (KG) has been realized, which could help to track the learning status of the students and recommend personalized study path. The application of KGs can effectively address the inability of traditional classroom instruction to precisely analyze student learning data. The system extracts knowledge points from answer records and maps them onto the course knowledge graph. Subsequently, leveraging the semantic hierarchical relationships and knowledge point sequences within the graph, it provides personalized knowledge point recommendations for students (Lang & Wang, 2020). Research has demonstrated that GSA, the progressive learning guidance system based on a course knowledge graph, significantly enhanced students' efficiency in both intra-curricular learning and cross-curricular development (Dong et al., 2023). Moreover, by transforming the KGs of learning materials into a three-dimensional network structure for student exploration in a mixed reality (MR) environment, the approach was favored by users across metrics including memory retention, ease of use, and technology acceptance (Hensen et al., 2023). Furthermore, the application of KGs enhances visualization and increases the flexibility of user interface design (Homola et al., 2023). In addition, KGs serve to consolidate educational resources by structuring the content and interconnections of chapters, sections, and key concepts. This addresses both the demand for personalized student learning and the need for teachers to deliver focused, tailored teaching (Sun, 2025).

Practical Simulation

Applied talent cultivation is a central focus in higher education. AI-powered virtual simulation technology empowers practical teaching by offering a variety of simulated scenarios. 5 out of the 10 case studies retrieved in this review (Table 1) were about the AI-enhanced simulation for experiments (Calzada et al., 2025; Li et al., 2025; Liu et al., 2025; Wang et al., 2025; Zhao et al., 2023). Students can conduct complex material experiments in virtual settings, which mitigates risks arising from physical constraints or procedural mistakes, while increasing experimental repeatability and efficiency. Through an intelligent assessment system that delivers immediate feedback, pinpoints errors, and suggests corrections, students are able to refine their techniques and strengthen practical competencies in a timely manner (Liang et al., 2025). In earlier research (Jormanainen et al., 2018), scholars employed an IT and AI-driven smart environment to monitor campus indicators such as water and electricity consumption, temperature, and CO₂ concentration for calculating carbon footprints. The resulting data then served as a basis for instructors to design relevant assignments or projects. The voice-controlled AI-CO₂ fountain experiment (Oh & Kang, 2021) lowered the barrier to conducting the experiment, facilitated students' conceptual understanding, and ensured experimental safety. To address the disconnect between traditional synthesis projects in undergraduate organic chemistry and the practical work of chemists, an online learning program has developed a more contextually relevant organic synthesis project (Healy & Blade, 2020). This project, accessible through a fully interactive platform equipped with advanced AI models, focuses on pharmacologically relevant and high-interest molecules while adapting to the online teaching format. It is designed to enhance relevance, while also exploring the pedagogical and technical challenges of online education, alongside concerns regarding student engagement.

Practical training in environmental fields often involves large-scale scenarios, such as soil remediation and water treatment projects, as well as exposure to toxic and hazardous pollutants. Virtual simulation experiments can overcome these barriers by making such hands-on projects considerably more feasible to implement. For example,

an entry-level lab-based undergraduate environmental chemistry course helped students to engage in research projects of Alaskan Arctic environmental issues through the combination of virtual and lab experiments (Guerard & Hayes, 2018). However, conventional virtual simulation models often exhibit inflexibility, and fall short of delivering the dynamic and immersive experiences essential for effective learning (Murali et al., 2024). Therefore, incorporating AI within the virtual simulation experiment by developing an interaction model holds the potential to significantly enhance interactivity and provide diverse possibilities for experimental exploration. In environmental research, the use of AI for prediction and simulation has a well-established history (e.g., (Cossentino et al., 2003)). Moving forward, there is potential to adapt these mature models for experimental simulation in teaching, thereby addressing the growing demand for cultivating novel practical skills.

Intelligent Assessment and Feedback

Timely classroom assessment and feedback enable teachers to identify areas where students struggle and adjust their instructional strategies, thereby improving teaching quality. The widespread adoption of AI in education presents an opportunity to further enhance grading and feedback processes (Abiad et al., 2025). Currently, online grading systems are capable of rapidly and accurately assessing objective questions such as multiple-choice and true/false items, thereby effectively reducing the time instructors spend on marking. “Stemle”, an AI-powered grading system designed for chemistry laboratory courses (Abiad et al., 2025), was capable of providing feedback on both closed-ended and open-ended prompts, thereby saving instructors’ time. It delivered detailed evaluative comments with a measurable degree of reliability. In addition, a teaching assessment mode powered by big data and AI could capture and interpret student behavioral data such as head orientation, facial features, and body posture. This model could thereby evaluate learners’ emotional responses and measure their engagement in digital learning environments (Li & Zhan, 2020). Intelligent assessment and feedback tools have been implemented across various disciplines. Researchers have developed a machine learning-based monitoring method to evaluate student academic performance, which consists of two phases: modeling and diagnosis. This approach effectively analyzed the grade data of software engineering students to identify the most suitable learning patterns for individuals (Liubchenko et al., 2024). An automated scoring system utilizing ChatGPT was capable of grading students by evaluating their operational steps and answers provided (Zhou et al., 2024). Machine learning has also been deployed to build a predictive model that evaluates teaching effectiveness through parameters like network accessibility and student engagement in digital learning, in order to generate quantitative forecasts (El-Sofany & El-Seoud, 2024). However, empirical case studies of intelligent assessment and feedback focused on environmental discipline remain unreported in the existing literature. The environmental science curriculum comprises theoretical courses (such as ecology, soil science, and environmental chemistry), involves hands-on laboratories (like microbiology and chemistry experiments), and requires comprehensive practical projects (e.g. environmental monitoring). Therefore, integrating AI into environmental education through intelligent assessment and feedback systems is expected to achieve similar effects comparable to those in other disciplines.

Prominent Advantages of AI-powered Teaching

Across all included cases, the benefits of AI integration in environmental education can be summarized along several coherent dimensions. Firstly, AI enables personalized learning (Calzada et al., 2025) by continuously monitoring student progress and delivering adaptive feedback. This capability allows the system to tailor instructional support to individual learning needs, thereby promoting targeted academic development and accommodating diverse learner profiles within environmental science curricula.

Secondly, by leveraging visual analytics, virtual simulation, and interactive knowledge representation, AI significantly enhances student engagement (Calzada et al., 2025; Li et al., 2025; Santiago, 2025; Zhao et al., 2023). Students are more likely to remain motivated when complex environmental concepts are presented in accessible and interactive formats. These technologies improve the intuitiveness of learning content and enrich the overall learning experience, leading to better comprehension and higher academic performance (Christina et al., 2025; Wang et al., 2025; Zhao et al., 2023).

Third, in instructional assessment and management, AI-powered tools support real-time learning diagnostics, automated grading and data-driven evaluation. These functions not only boost teaching efficiency but also substantially reduce educators’ administrative workload, freeing time for more meaningful teacher-student interaction and pedagogical refinement.

Fourth, AI applications strengthen the development of higher-order cognitive skills. Specifically, they foster critical thinking, problem-solving, and collaborative abilities, particularly within data-intensive environmental tasks and inquiry-based learning scenarios (Calzada et al., 2025; Lin et al., 2026; Liu et al., 2025; Zhao et al., 2023). By engaging with AI-assisted analysis and decision-making, students learn to navigate complex environmental challenges more effectively.

Fifth, the integration of virtual and physical learning environments expands instructional flexibility and inclusivity. AI facilitates remote learning opportunities, immersive practical activities, and a wider range of teaching formats (Christina et al., 2025; Wang et al., 2025). This blended approach accommodates different learning contexts and student needs, making environmental education more accessible and adaptable than traditional classroom-only models.

However, owing to the current paucity of empirical investigations, the synthesis of available case studies does not allow for the conclusive confirmation of all the advantages outlined above. Consequently, further research and more comprehensive data are urgently needed to substantiate the particular performance of AI integration within environment-related curricula.

Current Limitations and Challenges

General Challenges

Despite the considerable benefits of AI-powered teaching and learning, several notable challenges also exist in real-world educational practice. First of all is insufficient willingness or capability to use AI tools. The engagement of students with AI teaching tools shows significant disparity (Sousa & Cardoso, 2025), while instructors generally maintain a cautious stance, linking their adoption intent closely to the tools' practical pedagogical utility (Miranda & Chamorro-Mera, 2025). Both students and teachers require a period of adaptation and learning (Lavado-Anguera et al., 2025), especially for the those in the environmental disciplines who may not be familiar with the computation or AI techniques. Furthermore, trust in the efficacy of AI technology and users' own operational proficiency are key factors influencing their willingness to utilize these tools (McCarthy et al., 2025).

Secondly, data and model bias are one of the most critical general challenges that requires continued attention. The environmental data used to train AI systems may suffer from sampling bias. For instance, more complete learning data often comes only from highly engaged students, while some may provide fabricated data that does not reflect their true performance. Such biases can compromise the generalizability of pedagogical conclusions derived from AI analysis.

Thirdly, the absence of established ethical norms remains a key challenge. The digital divide and equitable access are major worries for users. Data privacy protection and the acquisition of informed consent highlight the importance of responsible AI use in educational settings (Lavado-Anguera et al., 2025). At the same time, excessive reliance on and misuse of AI tools pose a serious challenge to academic integrity (Ghimire et al., 2024). This is closely linked to students' insufficient awareness of ethical tool use and the absence of effective guidance and control mechanisms in higher education (McCarthy et al., 2025). The concerns about integrity issues from teachers also affect their willingness to use these tools.

Specific Challenges for the Pedagogical Application of AI in Environmental Disciplines

In addition to the above-mentioned general challenges, there are some specific challenges for the teaching applications of AI, especially within environmental disciplines. One crucial issue is the constraints on the development of higher-order competencies. While AI primarily serves as a knowledge-based teaching assistant in education, it still requires teachers to undertake thorough instructional design preparations and cannot be relied upon solely for autonomous content generation (Fuhrmann & Niemetz, 2024). Additionally, when faced with tasks that demand the application of knowledge to create innovative solutions or test problem-solving abilities, AI often falls short. This reflects the limited role of AI tools in fostering competency development.

Accessibility of professional data and model accuracy represent another challenge for the pedagogical applications of AI in discipline-specific contexts. General-AI struggles to effectively address specific problems in environmental science, while specialized AI tools primarily face challenges such as copyright protection of

professional and industry data (Wu et al., 2024). Models applied in environmental fields often require extensive labeled data. Such data demands high quality, but it is often prone to gaps or significant noise during collection (Konya & Nematzadeh, 2024). Furthermore, the complex types of environmental data include text, images, and time-series. The preprocessing of such data is a time-intensive process that requires expert participation for accuracy enhancement.

The third challenge would arise from the “black box” nature of many AI systems. AI models primarily rely on mathematical algorithms, with internal decision-making processes that lack transparency and are difficult to trace (Konya & Nematzadeh, 2024). This hinders students’ understanding and learning of the fundamental mechanisms of environmental systems. It requires developers to incorporate physical knowledge to improve model interpretability. Furthermore, in teaching, instruction in foundational theories must not be neglected in order to strengthen students’ comprehension.

Finally, the risk of diluting or replacing practical experience should be noted. While AI effectively simulates practical scenarios that are costly, hazardous, or geographically inaccessible to provide students with valuable training and conceptual understanding, such simulation cannot fully replace real-world field investigations and hands-on laboratory work. On one hand, the complex environmental variables, unstructured problem-solving, and sensory experiences involved in fieldwork are difficult to fully replicate through digital interfaces. On the other hand, actual laboratory operations not only train students in hand-eye coordination and instrument use but also cultivate an intuitive sense of error, adaptability to unexpected situations, and rigorous experimental habits. These competencies cannot be fully developed through virtual simulation alone.

Perspectives for Future Development

Research Gaps

Despite the growing literature on AI in education, several critical research gaps remain to be addressed. First, the ethical governance of AI applications in educational contexts remains under-explored. Key ethical issues such as data privacy protection, algorithmic bias mitigation, and decision-making transparency must be addressed to prevent AI applications from causing inequity or risks (Tomaskinova et al., 2025). How to enhance students’ ethical awareness in using AI tools and establish effective guidance and governance mechanisms in higher education institutions should be explored. Furthermore, the feedback ecosystem shaped by generative AI naturally intertwines with learners’ feedback literacy, affecting their overall responsiveness to input. Mechanisms such as cyclical self-regulated feedback frameworks can be employed to improve the interaction between AI and students’ feedback literacy, thereby mitigating model biases (Zhan et al., 2025). Second, more longitudinal and comparative empirical studies, that investigate the long-term effects and contextual differences of AI-enabled teaching and learning, are required. Due to the limited generalizability of AI tool effectiveness across different regions or groups, extensive long-term studies are required to demonstrate their actual impact on learning outcomes in environmental science.

Practical Recommendations

Beyond the aforementioned research gaps, greater efforts are needed to advance practical applications in the field. First, continuous tool development is essential to create more reliable, user-friendly, and context-adaptive systems for educational practice. It is advisable to develop AI-based teaching tools that better align with practical needs and are easy for instructors to adapt and use (e.g., learning analytics tools (Uukkivi et al., 2024)). Technical support should be improved to enhance willingness to adopt these tools and their effectiveness in practice (Xiang et al., 2025). Furthermore, specialized AI tools tailored to specific disciplines or courses could be developed to support domain-specific knowledge acquisition and skill training, thereby meeting the deeper demands of diverse teaching scenarios.

Second, targeted teacher development programs should be designed to enhance educators’ digital literacy and instructional capabilities. With the growing demand for instructors with “AI+” teaching competence, it is crucial for universities to foster emerging engineering talent among faculty and cultivate their ability to integrate AI into environmental innovation practices (Liu et al., 2025). This can be advanced by establishing interdisciplinary communities (environmental experts + educational technologists + AI researchers), thereby promoting deep integration across knowledge, skills, and environmental dimensions (Tomaskinova et al., 2025; Liu et al., 2025). Additionally, organizing seminars, workshops, and training sessions would help raise teachers’ willingness and

capacity to use AI-based teaching tools (Tomaskinova et al., 2025; Miranda & Chamorro-Mera, 2025; Xiang et al., 2025).

Third, clear and operational usage guidelines must be established to standardize the implementation of educational technologies. Universities should establish AI usage policies and ethical guidelines, clearly define the boundaries clearly between appropriate use and academic misconduct, and guide students to utilize tools rationally rather than over-relying on them (Ghimire et al., 2024). Assessment methods should be reformed by reducing dependence on single written assignments and strengthening process-oriented evaluation as well as practical competency assessment, thereby mitigating incentives for cheating at its root. Additionally, instruction should incorporate prompt engineering and AI literacy education to equip students with the ability to use generative AI efficiently and critically, such as judging the accuracy of AI outputs (Yuriev et al., 2024).

Last but not least, it is critical to ensure that technology applications remain true to the fundamental purpose and essence of education, putting student growth and educational values at the core. AI-empowered pedagogical design should remain grounded in the fundamental needs of education (Tomaskinova et al., 2025). It is essential to ensure that AI integration aligns with student-centered learning principles and curriculum design, supporting the implementation of innovative teaching methods rather than merely superimposing technology. Instructional activities should be designed following a “human-led, AI-assisted” approach, leveraging the efficiency of AI while preserving human creativity and critical thinking (Yuriev et al., 2024).

Conclusion

This study systematically reviews the pedagogical integration of AI in environmental disciplines based on 10 eligible empirical studies from WoS and Scopus, supplemented by transferable cases from related fields. The core application scenarios of AI in environmental education include virtual teaching assistants, personalized adaptive learning, practical simulations, and intelligent assessment and feedback systems.

The synthesis confirms AI’s transformative potential in enhancing personalized learning experiences, improving teaching efficiency, boosting student engagement, and facilitating data-driven instructional decision-making. However, existing studies consistently report limitations such as insufficient data quality, ethical and academic integrity concerns, uneven technical accessibility, and a lack of long-term validation. These challenges hinder deeper AI integration. More importantly, corresponding suggestions are proposed to promote the balanced development of generic AI technological advancement and its deep integration with discipline-specific teaching needs of environmental disciplines. Notably, while leveraging AI for innovation, we must not neglect foundational theories or real-world practice, both essential for talent cultivation in environmental disciplines.

Ultimately, this study provides a theoretical and practical basis for the rational application of AI in environmental education, aiming to support the modernization and high-quality development of environmental higher education. Although, this study may suffer notable limitations due to the limited number of eligible empirical studies and potential publication bias, more rigorous, longitudinal, and discipline-specific empirical research is urgently needed in the future to verify the practical benefits of AI applications in environmental education and address the existing constraints.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

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