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ARTIFICIAL INTELLIGENCE TOOLS, EDUCATIONAL APPROACHES, AND LEARNING OUTCOMES IN ENVIRONMENTAL EDUCATION

Özgün Arda Kuş

Abstract. *Artificial intelligence (AI) technologies are increasingly being used in environmental education, but the empirical evidence base in this field remains fragmented. The aim of this study was to systematically map empirical research on the use of AI in environmental education between 2022 and 2025. The study employed a scoping review design based on the PRISMA-ScR protocol. A total of 419 records retrieved from the Scopus and Web of Science databases were screened, and 16 studies met the inclusion criteria. Data were extracted using a structured coding framework based on four research questions and synthesized through thematic analysis. The findings indicated that large language models, particularly ChatGPT, are the most frequently used AI tools. Nine studies aimed to change attitudes or behaviors. Pedagogical approaches included content creation, personalized learning, narrative-based empathy development, and gamification. Only one study did not specify a clear theoretical framework. Standardized effect sizes were reported in only four studies. The geographical distribution was concentrated in East Asia. One study included a delayed post-test, leaving the long-term sustainability of the reported effects largely uncertain. Longitudinal designs, comparative tool evaluations, and culturally embedded AI designs from underrepresented regions have been identified as priority research needs for the field's advancement.*

Keywords: *artificial intelligence, environmental education, ChatGPT, scoping review, knowledge-action gap, pedagogical approaches, sustainability education*

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Introduction

Over the last decade, digital technologies have increasingly shaped educational practices across a wide range of disciplines. Environmental education, which has traditionally been grounded in outdoor learning and place-based pedagogy, has also begun to respond to this transformation. As environmental problems become more multidimensional and urgent, educational approaches are likewise expected to evolve in ways that address emerging social, ecological, and technological realities (Lowan-Trudeau, 2023). Within this broader process of digital transformation, artificial intelligence (AI) has emerged as one of the most influential recent developments.

In contrast to earlier digital technologies, AI systems offer more dynamic and adaptive forms of support by generating text, producing images, analyzing data, and providing personalized feedback. The public release of large language models (LLMs), such as ChatGPT, at the end of 2022 accelerated both scholarly and practical interest in the educational uses of AI. In a systematic review of 138 studies focusing on AI in higher education, Crompton and Burke (2023) identified five major areas of implementation: assessment, prediction, AI assistants, intelligent tutoring systems, and student learning management. Together, these developments suggest that AI has created new opportunities for teaching and learning, while at the same time introducing new pedagogical and ethical questions for environmental education.

The integration of technology into environmental education has attracted growing academic attention. Lowan-Trudeau (2023) stated that the influence of digital technologies on this field had not been sufficiently addressed. Hajj Hassan et al. (2024) reviewed studies published between 2013 and 2023 and found that digital tools had a positive effect on environmental knowledge. Virtual reality and climate change topics had become central in the research agenda. Husamah et al. (2025) examined 21 peer-reviewed articles and showed that augmented reality, virtual reality, and mobile applications increased student engagement and pro-environmental behavior.

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Chang and Kidman (2023) explored how ChatGPT could be used in geography and environmental education. They indicated that AI could generate context-based explanations quickly. However, they also underlined the need for students to question AI-generated responses critically. According to a review study conducted by Koseoglu and Erten (2026), AI gives environmental education a more interdisciplinary character. These reviews suggest that while technology integration is accelerating, the specific role of AI requires more focused analysis.

One of the most persistent problems in environmental education is the gap between knowledge and behavior. Kollmuss and Agyeman (2002) showed that cognitive, emotional, and cultural factors all contribute to this disconnect. Portus et al. (2024) demonstrated that approaches based solely on knowledge transfer are insufficient to close this gap. This challenge is directly relevant to AI integration. AI tools excel at information provision. If the primary limitation is not a lack of information but the difficulty of translating knowledge into action, then the pedagogical value of AI must be assessed against this criterion. According to Thornhill-Miller et al. (2023), environmental education also provides a strong context for developing critical thinking, collaboration, and creativity. Maor et al. (2023) stated that projects addressing environmental issues were particularly effective at supporting these competencies.

AI Technologies in Environmental Education

AI technologies have been used for educational purposes at various educational levels and in different contexts (Durso & Arruda, 2022; Usak, 2024). Also, AI technologies used in environmental education are diverse and rapidly evolving. In environmental education, they have been used to supplement teaching materials, support collaborative inquiry, and serve as interactive research partners. For example, Huang (2018) examined a 16-week AI-supported program on 186 university students and found significant positive effects on environmental knowledge, attitudes, and values. The Artificial Intelligence of Things (AIoT) combines Internet of Things infrastructure with AI algorithms. These systems can collect real-time environmental data and present it to students in ways that connect abstract concepts to concrete evidence (Tabuenca et al., 2024).

The swift development of AI tools designed for visual content generation, exemplified by DALL-E, Midjourney, and Sora, has introduced novel possibilities for environmental education. These tools empower both educators and students to produce captivating visual scenarios that were once challenging or expensive to create (Shahzad et al., 2025; Rillig, 2024). A significant application of this technology is the creation of "what-if" climate visualizations. These AI-generated images can simulate possible future environmental conditions, such as showing a familiar area flooded by rising sea levels or obscured by wildfire smoke (Luccioni et al., 2021). Consequently, these personalized visual scenarios can make abstract environmental threats more tangible and emotionally impactful for students, thereby fostering greater engagement with sustainability concerns (Hopke, 2025). Likewise, AI-driven video generation tools have shown the capacity to produce educational content that elucidates complex ecological relationships and environmental processes, all at a fraction of the cost and time required by conventional video production methods (Rillig, 2024). In light of these developments, it is reasonable to assert that AI-based image and video creation tools possess considerable potential for enhancing environmental education through immersive and readily accessible visual experiences.

Koseoglu and Erten (2026) concluded that AI technologies increase environmental awareness by making environmental issues more accessible. Beyond awareness, research suggests that AI tools can influence emotional engagement and behavioral intentions. AI-supported content production also creates new opportunities. Students can move from passive receivers to active creators through tools that combine writing, visual design, and multimedia.

The integration of AI into environmental education raises ethical concerns. The Value-Sensitive Design framework (Friedman & Hendry, 2019) offers a systematic approach for embedding human values into technology design. UNESCO (2022) identified fairness, transparency, accountability, and privacy as core values for ethical AI use in education.

The environmental impact of AI is also a major cause for concern. Koseoglu and Erten (2026) have pointed out that a brief conversation with ChatGPT consumes approximately half a liter of water. When applied to billions of daily requests, this consumes a significant number of resources. This challenge clearly incorporates the ethical use of AI into the framework of environmental education. Chang and Kidman (2023) have expressed concerns regarding academic integrity. The Human-AI Cognition paradigm (Siemens et al., 2022) argues that educational design must emphasize tasks that AI cannot perform, including fieldwork, direct observation, and value-based reasoning. Garcia-Lopez and Trujillo-Linan (2025) showed that digital inequality is a structural issue of educational justice. Communities most affected by environmental problems often have the least access to quality AI-supported education.

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Purpose of the Study and Research Questions

The above review clearly demonstrates that the use of AI in environmental education is a rapidly growing topic. However, the evidence base regarding geography, methodologies, AI tools, and theoretical frameworks remains inconsistent. Previous evaluations have either examined digital tools in general (Hajj Hassan et al., 2024; Husamah et al., 2025) or have not provided a comprehensive PRISMA-ScR synthesis (Koseoglu and Erten, 2026). There is a need for a comprehensive scoping review that carefully maps the scope of real-world studies focusing on artificial intelligence in environmental education.

The aim of this study was to review all real-world studies published between 2022 and 2025 that examine the use of AI in environmental education. The review was conducted in accordance with the PRISMA extension for Systematic Reviews protocol (Tricco et al., 2018). The Scopus and Web of Science databases were used to find studies. The goal is to map the current state of the field, identify common trends among the studies, and highlight areas requiring further research. The review is based on the following research questions.

RQ1. Which AI tools were used in environmental education, what pedagogical roles did they serve, and what design philosophies guided their integration?

RQ2. What cognitive, affective, and behavioral learning outcomes were associated with AI-supported environmental education interventions?

RQ3. What methodological approaches, theoretical frameworks, and intervention designs characterized the current evidence base?

RQ4. What geographical patterns and contextual factors are visible in the literature, and what do they imply for educational equity?

Research Methodology

General Background

This study was designed as a scoping review to systematically map the use of AI in environmental education. The scoping review method was considered more appropriate than systematic reviews or meta-analyses for mapping research areas that are still evolving, methodologically heterogeneous, and theoretically diverse (Arksey & O'Malley, 2005). Because environmental education integrated with AI encompasses many different tools, research approaches, and learning outcomes, it was not possible to use a meta-analysis to synthesize them all. The scoping review method was used because it facilitates mapping the current state of the field, identifying key trends and patterns, and highlighting gaps for further research.

The study adhered to the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses of Scoping Reviews) guidelines (Tricco et al., 2018), which provide a 22-item checklist aimed at ensuring transparency and reproducibility in the reporting of scoping reviews.

Ten key questions were identified to guide data extraction from the included studies. These questions addressed the following dimensions: the purpose of the studies and research questions, the AI tools used, the purpose and role of these tools, the target audience and study groups, the dimensions of environmental education addressed, the measurement tools used, the contributions provided by AI, recommendations for future research, the preferred research method and approach, and the geographical distribution of the studies. These 10 questions served as operational coding dimensions for data extraction; each aligned with one or more of the five research questions.

Data Collection

The literature search was conducted in the Scopus and Web of Science (WoS) databases. These two databases were chosen because they are the most comprehensive multidisciplinary sources for indexing peer-reviewed academic publications in the social sciences, education, and technology (Mongeon & Paul-Hus, 2016). Together, they provide broad and complementary coverage of international research: Scopus offers wider journal coverage, especially for newer journals, while WoS provides more thorough coverage of journals with longer citation histories and higher impact factors. Using both databases reduced the risk of missing relevant studies that were only indexed in one source.

The review was limited to studies published between 2022 and 2025. This timeframe was selected in light of the public release of ChatGPT in November 2022, a significant technological milestone that marked the beginning

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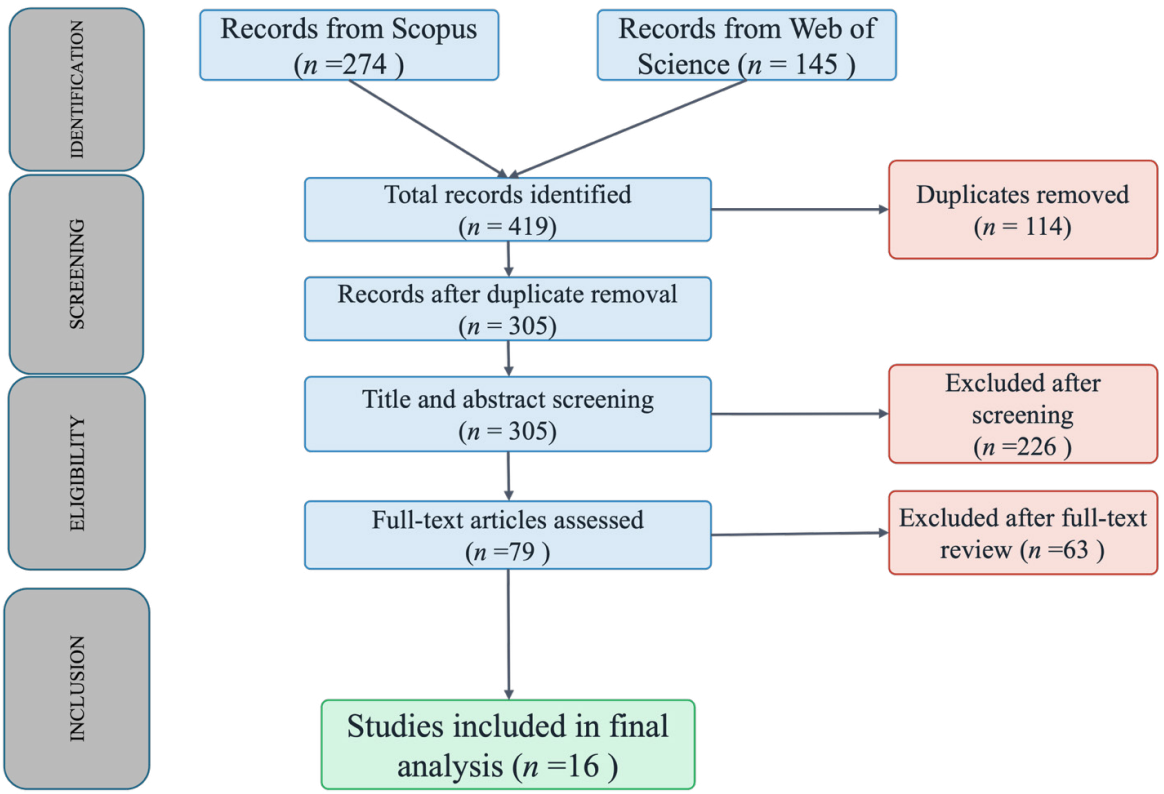
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of widespread access to large language models in educational settings. Prior to this date, there were virtually no empirical studies addressing LLM-based applications in environmental education. The year 2022 was therefore accepted as the starting point for examining the emergence and rapid growth of AI-integrated environmental education research.

The search query combined terms related to environmental education and artificial intelligence. For environmental education, the following terms were used: "environmental education," "environmental literacy," "sustainability education," "education for sustainable development," "climate change education," "ecological education," and "green education." For artificial intelligence, the terms included: "artificial intelligence," "AI," "machine learning," "natural language processing," "intelligent system," "chatbot," "conversational agent," "generative AI," "ChatGPT," "GPT," "large language model," "LLM," "intelligent tutoring system," "adaptive learning," "Claude," and "Gemini." A total of 274 records were obtained from the Scopus database and 145 records from WoS, resulting in a combined total of 419 studies.

After combining the records obtained from the two databases, 114 duplicate records were identified and removed. The remaining 305 studies were then subjected to title and abstract screening, which was conducted by the researcher. A total of 79 studies met the initial criteria and were included in the full-text review stage. At this stage, the full texts of the 79 studies were independently reviewed by the researcher and a colleague with expertise in educational research. Each reviewer assessed the studies against the predefined inclusion and exclusion criteria. Following independent evaluation, the two reviewers compared their decisions. Agreement was reached on 77 of the 79 studies (97.47%). Disagreement arose regarding two studies; after a detailed discussion of the relevance and scope of these studies, both reviewers reached consensus that the two studies did not sufficiently meet the inclusion criteria, and they were excluded from the final corpus. Inter-rater reliability for the full-text screening was calculated using Cohen's kappa coefficient, yielding $\kappa = .93$, indicating almost perfect agreement (Landis & Koch, 1977). As a result, 16 studies were retained for the final analysis. The details of the selection process are presented in the PRISMA flow diagram (Figure 1).

Figure 1
Data Collection Process (PRISMA-ScR)



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The inclusion criteria were defined as follows: the study must involve the use of artificial intelligence, address environmental education or one of its related subfields, have been published in 2022 or later, be written in English, and have been published as an article in a peer-reviewed journal or as a peer-reviewed conference paper. Studies that were purely theoretical in nature, lacking empirical data, were excluded.

Data Analysis

Data extraction from the 16 studies included in the final analysis was conducted using a structured coding framework developed in accordance with the five research questions. This framework consisted of ten coding dimensions: the study's purpose, the AI tools used, the pedagogical role of AI, the target audience, the environmental education dimensions addressed, the assessment tools, the contributions of AI to learning, recommendations for future research, the research methodology, and the geographical context. These dimensions were derived from the research questions and refined through pilot coding of three randomly selected studies.

The researcher first read each of the 16 studies in full and identified passages relevant to the research questions. These passages were recorded in a structured Excel table organized by study identifier and coding dimension. Initial codes were then assigned to each entry. Following this individual coding phase, the researcher and a colleague specializing in educational research jointly reviewed all codes and extracted passages. During this cooperative review, certain coding dimensions (For example, each study's research methodology, the AI tools used, and sample characteristics) required minimal discussion, as the classification was relatively straightforward. Other dimensions, particularly those related to AI's pedagogical role, theoretical frameworks, and learning outcomes, necessitated more detailed evaluation. Through mutual explanation and discussion, the researcher and colleague reached full consensus on the final codes.

The final codes were synthesized using thematic analysis, following the six-step approach outlined by Braun and Clarke (2006). After familiarization with the coded data, initial codes were grouped into potential themes based on recurring patterns. These candidate themes were reviewed against the coded passages and the full dataset to ensure internal consistency and external distinctiveness. The themes were then defined and named. The final thematic structure consisted of five themes aligned with the five research questions: (1) AI-supported cognitive and emotional development, (2) AI tools, pedagogical roles, and design philosophies, (3) methodological landscape and intervention quality, (4) theoretical and conceptual frameworks, and (5) geographical distribution and educational equity. The research findings were developed based on these themes, supported by frequency counts, cross-tabulations, and illustrative examples drawn from the included studies.

Research Results

Theme 1: AI-Supported Cognitive and Emotional Development

Raising environmental awareness was the most prevalent objective across the reviewed studies. It was addressed across a wide topical spectrum, covering medical waste (Kaya et al., 2025), water pollution (Palomino-Gamez et al., 2025), urban heat islands (Tabuenca et al., 2024), ecosystem fragility (Tumedei et al., 2025), climate change (Cao & Jian, 2024; Vázquez-Parra et al., 2025), and sustainability in rural design contexts (Yang, 2025). However, the more significant pattern concerned the growing ambition of outcome targets beyond knowledge acquisition alone.

Eight studies, or half of the total, examined changes in attitudes or behaviors as a main or secondary result. Four of these studies used environmentally friendly behavior as the main outcome they were measuring (Kaya et al., 2025; Cao and Jian, 2024; Arif et al., 2025; Koon Lin et al., 2025). However, it should be noted that Kaya et al. (2025) did not find a statistically significant improvement in medical waste attitudes and behaviors ($p > 0.05$); the significant effect in their study was limited to environmental awareness. These results indicate that researchers' focus is not limited to merely acquiring information. Studies are now designed to close the knowledge-action gap. Palomino-Gamez et al. (2025) and Vázquez-Parra et al. (2025) addressed this gap in their work. Their narrative-based AI model, Alma de Tezontle, attempted to bridge it through empathy and dialogic recognition rather than information delivery. The researchers' findings were noteworthy. Significant changes were observed across three areas: a decrease in beliefs about minimizing environmental impact ($p < 0.0001$), an increase in pro-environmental behaviors ($p = 0.0003$), and an increase in anxiety about the climate crisis ($p = 0.0031$). These effects, which came from a single-session intervention, show that carefully designed short-term experiences, especially those using personalized narratives, can lead to measurable immediate changes.

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Tumedei et al. (2025) also obtained similar results: interactive systems that combined children's drawings with a chatbot helped children understand the poor condition of the Mar Menor lagoon by 33.3% and the cause of climate change by 23.1%. This finding was particularly interesting because the "desire to take action" only emerged as a theme after the children had spoken with the chatbot. Children who had previously shown no interest in doing anything for the environment began asking questions such as "How can we help Mar Menor?" and "What do you want us to do?". This trend suggests that AI-mediated empathetic communication can serve as a catalyst for moving beyond awareness toward behavioral intent.

A third cluster emerged in four studies (25%): metacognitive and 21st-century competencies. Arif et al. (2025) introduced ecological intelligence as a distinct construct. Koon Lin et al. (2025) evaluated prompt literacy as an outcome of environmental education in their study. Yang's (2025) research demonstrated the capacity of AI tools to support self-regulated learning and critical thinking within the context of sustainability-oriented design initiatives. The findings indicated a substantial enhancement in environmental awareness, with over 85% of the student cohort exhibiting increased understanding. Furthermore, the study revealed that resource efficiency was a characteristic of more than 70% of the design proposals submitted by the students. Collectively, this research broadens the field's understanding of the implications of environmental learning. The focus shifts from declarative knowledge toward higher-order thinking, systemic reasoning, and responsibility attribution. Vázquez-Parra et al. (2025) took this furthest by targeting structural responsibility rather than individual behavior change.

Gender differences in AI-mediated environmental learning represent an underexplored dimension that emerged from the data. Palomino-Gamez et al. (2025) found that female participants in the experimental group were more worried about the global warming crisis and acted in ways that were good for the environment. But male participants were less likely to believe that the environmental problem was not as bad as it really is. This differing pattern indicates that the gender variable must be considered when planning and assessing AI-driven educational initiatives aimed at ecological awareness.

Table 1
AI-Supported Cognitive and Emotional Development: Coding Scheme

Sub-theme	Code	*n*	References
1.1 Environmental Awareness (11 studies, 68.8%)	Medical waste awareness	1	Kaya et al. (2025)
	General environmental awareness	3	Cao & Jian (2024); Uyanık (2025); Xiaoyu et al. (2025)
	Ecosystem fragility awareness	1	Tumedei et al. (2025)
	Water pollution / environmental crisis	1	Palomino-Gamez et al. (2025)
	Climate change awareness	2	Cao & Jian (2024); Vázquez-Parra et al. (2025)
	Sustainability awareness	2	Sun & Hsiao (2025); Yang (2025)
	Environmental literacy	1	Xiaoyu et al. (2025)
	AIoT-based awareness	1	Tabuenca et al. (2024)
1.2 Attitude and Behavior Change (8 studies, 50%)	Attitude change	3	Kaya et al. (2025); Cao & Jian (2024); Palomino-Gamez et al. (2025)
	Behavioral change	4	Kaya et al. (2025); Cao & Jian (2024); Arif et al. (2025); Koon Lin et al. (2025)
	Knowledge-action gap	2	Palomino-Gamez et al. (2025); Vázquez-Parra et al. (2025)
	Attribution of responsibility	1	Vázquez-Parra et al. (2025)
1.3 Metacognitive and 21st-Century Skills (4 studies, 25%)	4C skills	1	Sachyani & Gal (2025)
	Metacognitive processes / self-regulation	1	Yang (2025)
	Critical thinking / problem solving	2	Yang (2025); Santiago (2025)
	Ecological intelligence	1	Arif et al. (2025)
	Prompt literacy	1	Koon Lin et al. (2025)

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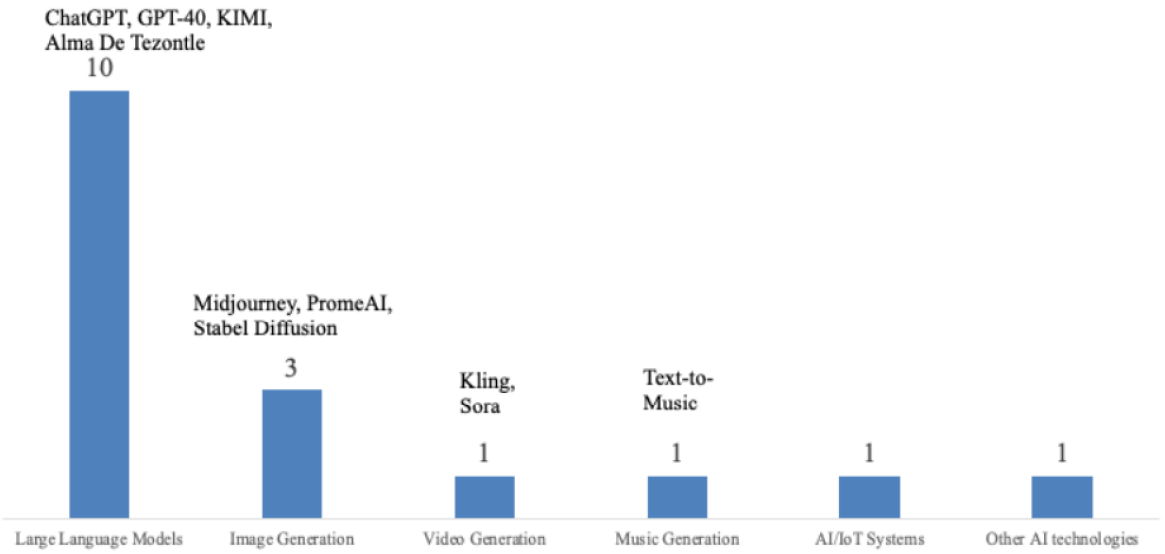
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Theme 2: AI Tools, Pedagogical Roles, and Design Philosophies

LLMs constituted the most frequently used tool category, appearing in 10 studies (62.5%) (As shown in Figure 2). Within this category, ChatGPT and GPT-family models were used in nine instances. Yang (2025) was the only study that employed a different LLM, using KIMI within an art and design education context. No study directly compared the effectiveness of different LLM platforms for the same educational purpose.

Image generation tools were the second most widely adopted category, appearing in three studies (18.8%). Only one study (Koon Lin et al., 2025) considered tools for making videos. One study (Tabuenca et al., 2024) used AIoT systems that needed sensor arrays, IoT infrastructure, and data pipelines. Virtual reality appeared in one study (Cao & Jian, 2024) and required dedicated hardware. One study (Yang, 2025) used AI evaluation frameworks, notably the Ragas framework, to fully evaluate the sustainability of student designs. The distribution of tools has revealed a range of implementation challenges. While tools that do not require extensive technical knowledge are used more frequently, those requiring specialized infrastructure have been used in only a few studies.

Figure 2
AI Tool Categories



The two most common teaching methods have been content creation and personalized learning. Seven studies (43.8%) focused on text creation (Uyanık, 2025), sustainability recommendations (Sun & Hsiao, 2025), environmental poetry (Koon Lin et al., 2025), comic book and song creation (Sachyani & Gal, 2025), rural design visualization (Yang, 2025), and climate-related video production (Koon Lin et al., 2025). Four studies (25%) focused on personalized learning, which can encompass everything from adaptive content delivery (Cao and Jian, 2024; Xiaoyu et al., 2025) to individualized feedback (Arif et al., 2025; Yang, 2025).

Narrative and empathy development represented a pedagogically distinctive approach without clear counterparts in other educational fields. Three studies adopted this strategy. Tumedei et al. (2025) designed a system in which children directly interacted with the Mar Menor lagoon as a sensitive interlocutor. The AI was instructed to interpret the lagoon itself, speaking in the first person about its ecological value and vulnerabilities. Children could pose questions via voice or keyboard and receive both spoken and written responses. The Alma de Tezontle model (Palomino-Gamez et al., 2025; Vázquez-Parra et al., 2025) used a six-stage personalization methodology: search and collection of information from life stories, content curation and selection, loading and configuration of instructions, building the GPT's personality, maintaining dialogue and thematic coherence, and testing and optimizing the dialogue. The model adopted the voice of an ancient stone located on the banks of the Santiago River, one of Mexico's most polluted bodies of water. These approaches treated the emotional bond with the non-human world as a prerequisite for genuine environmental literacy rather than an add-on to cognitive learning.

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Gamification strategies were employed in two studies. Tabuenca et al. (2024) established a clear link between how students behaved and how the environment changed by linking the lifespan of the Plantagotchi avatar to the air quality in the classroom. Sun and Hsiao (2025) made abstract greenhouse gas indicators more understandable by using a carbon credit system.

Table 2
Pedagogical Use Cases and Objectives of AI Tools

Purpose	Strategy	n	Application Examples
Content Creation	Text / story creation	4	Uyanık (2025); Sun & Hsiao (2025); Koon Lin et al. (2025); Yang (2025)
	Visual production	3	Yang (2025); Koon Lin et al. (2025); Sachyani & Gal (2025)
	Video creation	1	Koon Lin et al. (2025)
	Music synthesis	1	Sachyani & Gal (2025)
Personalized Learning	Adaptive content	2	Cao & Jian (2024); Xiaoyu et al. (2025)
	Individual feedback	3	Arif et al. (2025); Yang (2025); Sun & Hsiao (2025)
Narrative and Empathy	Story-based dialogue	3	Palomino-Gamez et al. (2025); Vázquez-Parra et al. (2025); Tumedei et al. (2025)
	Anthropomorphization	2	Tumedei et al. (2025); Vázquez-Parra et al. (2025)
Gamification	Gamification	2	Tabuenca et al. (2024); Sun & Hsiao (2025)
Collaborative Learning	Group / async support	3	Santiago (2025); Sun & Hsiao (2025); Koon Lin et al. (2025)
Evaluation	Auto evaluation / data analysis	3	Yang (2025); Nguyen et al. (2025); Tabuenca et al. (2024)
Behavior Tracking	Action tracking	1	Arif et al. (2025)

The most significant analytical finding in this study was the identification of three distinct design philosophies that shape how AI is used in environmental education. The most common way to use AI was as a content enrichment tool (8 studies, 50%). In these experiments, AI was used to create supplementary materials, answer questions from students, or support existing lesson plans. ChatGPT served as an additional resource that did not alter the way teachers and students interacted with one another.

The second level, AI as a personalized learning system, was observed in four studies (31.2%). Yang (2025) employed a three-phase AI integration model: language model for exploration (KIMI), generative tools for design (Midjourney, PromeAI, Stable Diffusion), and an evaluation model for feedback (Ragas). Cao and Jian (2024) combined AI chatbots with VR to create adaptive environmental experiences. At this level, AI adapted to individual learners and provided real-time feedback, representing a qualitative shift from static content delivery.

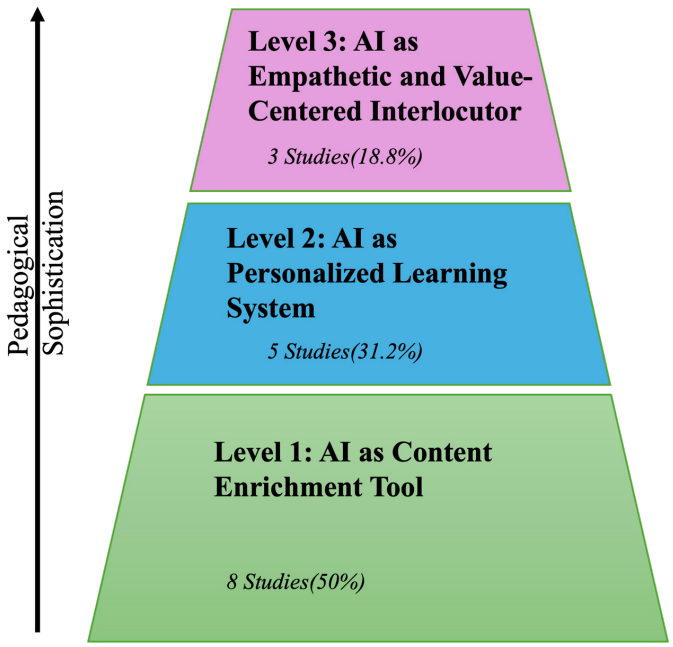
The third and most sophisticated level was AI as an empathetic and value-centered interlocutor. This level appeared in three studies (18.8%). Palomino-Gamez et al. (2025) and Vázquez-Parra et al. (2025) developed a culturally embedded GPT persona based on the ecological and cultural history of the Santiago River basin. Nguyen et al. (2025) designed five different chatbot personas through Value-Sensitive Design. Each persona reflected a different stakeholder perspective on environmental issues. Tumedei et al. (2025) created a system in which an AI-powered lagoon spoke to children in the first person about its ecological fragility. In this system, children's own drawings were used as interactive triggers. At this level, AI was presented not as a generic source of information, but as an empathetic interlocutor. Its purpose was to support emotional connection, ethical reflection, and a deeper understanding of the structural dimensions of environmental crises.

This distinction was educationally consequential. Environmental issues involve contested values, unequal power relations, and structural injustice. Generic AI tools were poorly equipped to address these dimensions without deliberate pedagogical design. The use of Value-Sensitive Design, narrative personalization, and multi-perspective representation provided concrete responses to this limitation.

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Figure 3
Design Philosophies: A Three-Level Typology of AI in Environmental Education



Xiaoyu et al. (2025) conducted a study that provides a comprehensive critical assessment of the shortcomings of artificial intelligence technologies in environmental education. The study utilized an intuitive analysis conducted by three experts in the fields of environmental science, artificial intelligence, and educational technology, which revealed significant usability concerns. For example, in the error prevention dimension, a severity score of 2.6 out of 4 was assigned, indicating a significant usability issue. Error prevention and alerting capabilities are absent from ChatGPT's user interface, according to the experts. Error recovery, help documentation, the system's compatibility with the real world, and flexibility and efficiency of use were identified as minor usability issues.

Semi-structured interviews with seven undergraduate students revealed additional concerns. Students noted that ChatGPT frequently provided basic and simplistic knowledge that lacked depth for advanced environmental topics. Language accessibility barriers were identified for non-English speakers, and the absence of multimedia resources (video, interactive elements) limited the learning experience. Despite these limitations, the system received high usability scores (SUS = 87.50, CUQ = 82.8), and students appreciated its intuitiveness and capacity for self-directed learning. This duality between high general usability and specific pedagogical limitations highlights the need for hybrid models that combine AI efficiency with human educator judgment, a conclusion that Xiaoyu et al. (2025) explicitly recommended.

Theme 3: Methodological Landscape and Intervention Quality

The 16 studies showed considerable methodological diversity, and no single research design was dominant. Quasi-experimental designs were used in five studies (31.3%) to support causal claims (Kaya et al., 2025; Uyanık, 2025; Palomino-Gamez et al., 2025; Vázquez-Parra et al., 2025; Cao & Jian, 2024). However, none of these studies used true random assignment. Instead, they relied on existing class groups, which increased the risk of selection bias. Four studies (25%) used case study designs. Mixed-methods designs appeared in three studies (18.8%). Action research was used in two studies (12.5%), and two studies (12.5%) adopted design-based approaches.

Advanced analytical techniques were used in a small subset. Cao and Jian (2024) used structural equation modeling. Vázquez-Parra et al. (2025) employed machine learning decision trees. Tabuenca et al. (2024) applied

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ARIMA time-series forecasting and machine learning algorithms. Palomino-Gamez et al. (2025) used permutation-based nonparametric tests with the maxT statistic, a robust approach for non-normal distributions common in attitude research. These techniques were used as research analysis tools rather than pedagogical interfaces. No study positioned machine learning as a tool for direct interaction with students.

Table 3
Methodological Approaches and Research Designs

Main Methodology	Sub-category	n	References
Experimental / Quasi-Experimental	Pre-post with control	4	Kaya et al. (2025); Uyanık (2025); Palomino-Gamez et al. (2025); Vázquez-Parra et al. (2025)
	Between-groups	1	Cao & Jian (2024)
Case Study	Single case	3	Sachyani & Gal (2025); Arif et al. (2025); Huang & Chang (2024)
	Multiple case	1	Tabuenca et al. (2024)
Mixed Methods	Explanatory sequential	1	Uyanık (2025)
	Qual-quant integration	2	Xiaoyu et al. (2025); Koon Lin et al. (2025)
Action Research	CAR / Practical AR	2	Santiago (2025); Yang (2025)
Design / Development	Research through Design	1	Tumedei et al. (2025)
	Value-Sensitive Design	1	Nguyen et al. (2025)
Sample Size	Small (n < 50)	4	Arif (30); Sun & Hsiao (29); Sachyani & Gal; Yang (26)
	Medium (50–200)	4	Kaya et al.; Uyanık; Palomino-Gamez / Vázquez-Parra (92); Huang & Chang (59)
	Large (200+)	2	Cao & Jian (375); Santiago (214)

Note. Palomino-Gamez et al. (2025) and Vázquez-Parra et al. (2025) share the same sample (N = 92). CAR = Collaborative Action Research.

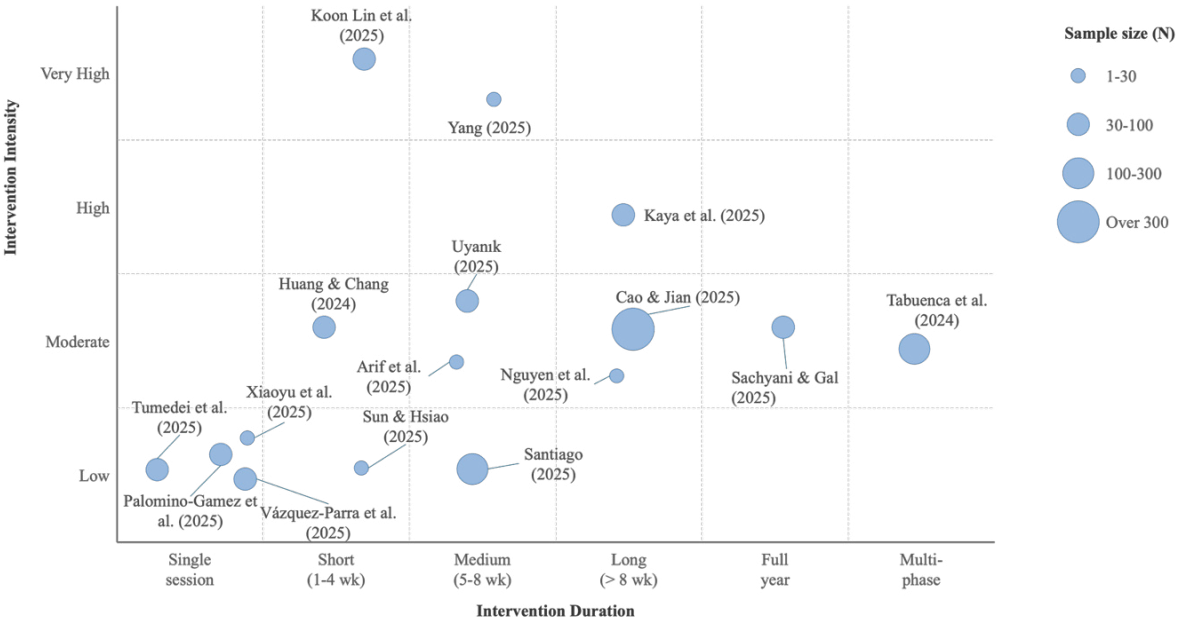
Four studies (25%) involved fewer than 50 participants. Four studies (25%) used medium-sized samples of 50 to 200 participants. Two studies (12.5%) used large samples of more than 200 participants: Cao and Jian (2024) had 375 participants, while Santiago (2025) had 214. Six studies (37.5%) did not explicitly state the number of participants. Palomino-Gamez et al. (2025) and Vázquez-Parra et al. (2025) used the same sample of 92 participants (60 experimental, 32 control) but investigated different dependent variables; this is a factor that must be considered when analyzing patterns at the meta-analysis level. Huang and Chang (2024) documented 59 participants and were therefore categorized as a medium-scale study.

The duration of the interventions varied greatly. Koon Lin et al. (2025) and Yang (2025) implemented the most intensive programs, which required 72 hours of contact time over a six-week period. On the other hand, Palomino-Gamez et al. (2025) and Vázquez-Parra et al. (2025) used single-session designs lasting approximately one to two hours. Both single-session studies showed statistically significant changes in environmental awareness. Palomino-Gamez et al. reported significant effects in three of the seven measured dimensions. These findings suggest that well-designed short-term interventions based on story personalization can produce measurable immediate outcomes. However, the long-term persistence of these effects has not yet been examined.

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Figure 4
Intervention Duration and Intensity Matrix



A notable methodological finding was the almost complete absence of delayed post-tests across the corpus. Of the 16 studies, only Koon Lin et al. (2025) conducted a follow-up assessment. They conducted a delayed final assessment three months after the intervention and examined retention across four domains: retention of technical skills (87.3%), environmental awareness (92.2%), cultural sensitivity (78.4%), and community participation (64.7%). The remaining 15 studies reported results only immediately following the intervention, regardless of duration, and excluded subsequent follow-up measurements. As a result, the sustainability of most reported effects remains unclear. Environmental education research has consistently shown that lasting changes in behavior and attitudes require ongoing reinforcement over time. Without follow-up data, it is difficult to determine whether the reported outcomes reflect genuine learning or only temporary participation effects in most of the reviewed studies. The findings of Koon Lin et al. (2025) further highlight this issue. Their results showed different retention rates across dimensions, with the sharpest decline in community engagement. This points to the need for delayed assessments in future research. Therefore, this issue should be seen not only as a methodological limitation but also as an empirical blind spot with direct implications for policy implementation.

Theme 4: Theoretical and Conceptual Frameworks

The theoretical foundations of the 16 studies varied considerably. Only one study (6.3%) did not present an explicit theoretical framework (Kaya et al., 2025). This study took an intervention-focused approach and measured outcomes without identifying a guiding theory. Two other studies first appeared to be atheoretical, but closer examination showed that they were in fact grounded in identifiable theoretical perspectives. Cao and Jian (2024) based their study on a structured model tested through structural equation modeling with four explicit hypotheses, drawing on environmental behavior theory. Uyanık (2025) used the Human-ChatGPT Collaborative Learning Model and referred to Constructivist Learning Theory (Piaget, Vygotsky) as the pedagogical foundation. Although studies without an explicit theory can still provide useful descriptive findings, they cannot explain why an intervention works or under which conditions it may be replicated.

The most theoretically developed studies used clearly defined frameworks. Nguyen et al. (2025) applied Value-Sensitive Design through a three-part structure that included empirical, conceptual, and technical dimensions. Their conceptual model directly informed the chatbot features, making this a rare example of strong alignment between theory and practice. Yang (2025) grounded the study in metacognitive theory and action research methodology and

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systematically connected the use of AI tools to self-regulated learning processes. Palomino-Gamez et al. (2025) used a validated GPT Personalization Methodology based on Life Stories and Dialogue for the Development of Empathy and Recognition. This approach grounded the intervention in recognition theory and empathy-based pedagogy.

The body of research also reveals a geographical pattern in theoretical preferences. Studies conducted in the People's Republic of China have predominantly employed behavioral change and motivation frameworks linked to measurable outcomes. Value-based and ethical design frameworks have been used more frequently in studies from Europe and North America. Studies in Latin America stand out for their focus on empathy, recognition, and structural accountability as fundamental theoretical principles. These differences likely stem from distinct research cultures, financial objectives, and differing perspectives on the purpose of environmental education. Therefore, any effort to develop a unified theoretical framework for AI in environmental education will need to take these epistemological differences into account.

Table 4
Theoretical and Conceptual Frameworks Used in Included Studies

Category	Theory / Model	n	Studies	Key Concepts
Pedagogical Theories	Transformative learning	1	Arif et al. (2025)	Sustainability through transformative experiences
	Socioformative pedagogy	1	Vázquez-Parra et al. (2025)	Ethical reflection, transdisciplinary knowledge
	Collaborative learning	2	Santiago (2025); Sun & Hsiao (2025)	Asynchronous collaboration, peer platforms
	Action research / Metacognition	1	Yang (2025)	Self-regulated learning, critical reflection
Motivation	ARCS Model	1	Huang & Chang (2024)	Attention, Relevance, Confidence, Satisfaction
	Gamification principles	1	Tabuenca et al. (2024)	Avatars, feedback loops
Design Frameworks	Value-Sensitive Design	1	Nguyen et al. (2025)	Empirical, conceptual, technical dimensions
	Research through Design	1	Tumedei et al. (2025)	Nature activity, system design, school testing
	GPT Personalization Methodology	2	Palomino-Gamez et al.; Vázquez-Parra et al.	Life stories, empathy, dialogic recognition
	IDEE Framework	1	Santiago (2025)	Identification, Determination, Ethics, Evaluation
Skill Development	21st Century Skills (4Cs)	1	Sachyani & Gal (2025)	Creativity, Critical Thinking, Collaboration, Communication
	Ecological intelligence	1	Arif et al. (2025)	AI for ecological awareness in early learners
	Prompt literacy	1	Koon Lin et al. (2025)	Writing as coding for sustainability
Environmental Psychology	Empathy and recognition	2	Palomino-Gamez et al.; Vázquez-Parra et al.	Valuing the other as subject with dignity
Technology Integration	AIoT	1	Tabuenca et al. (2024)	Sensor-AI integration for real-world data
	Environmental Behavior Theory	1	Cao & Jian (2024)	SEM-based environmental behavior model, hypothesis testing
	Human-ChatGPT Collaborative Learning / Constructivism	1	Uyanık (2025)	Piaget, Vygotsky, AI-mediated collaborative learning
No Explicit Framework	Atheoretical	1	Kaya et al. (2025)	Intervention-focused, outcome measurement without guiding theory

Theme 5: Geographical Distribution and Educational Equity

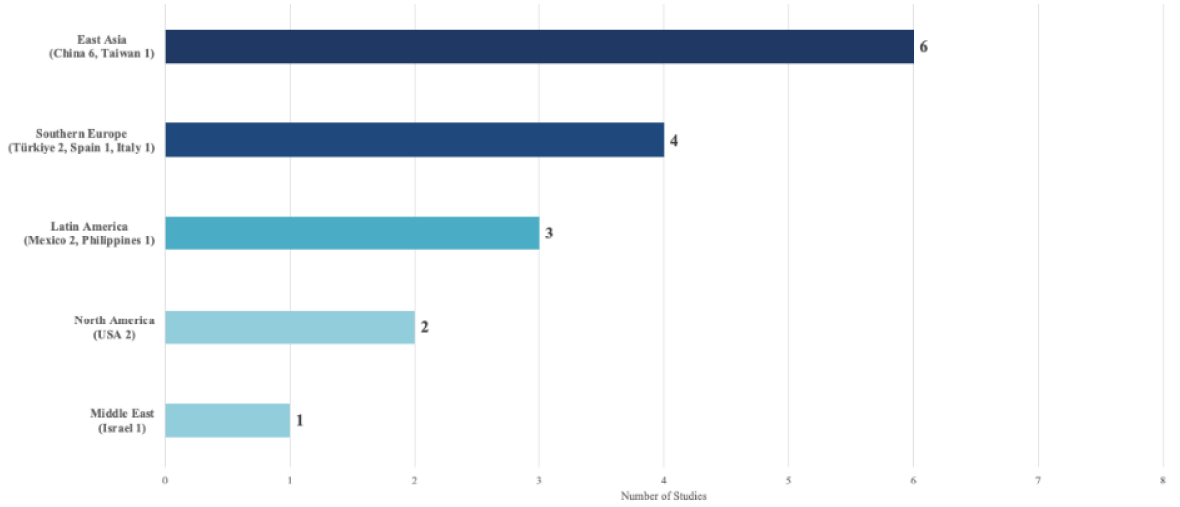
The geographical distribution revealed a pronounced asymmetry. East Asia, particularly the People's Republic of China, accounted for six of the 16 studies (37.5%). This included studies conducted in mainland China (Cao & Jian, 2024; Arif et al., 2025; Yang, 2025; Xiaoyu et al., 2025; Huang & Chang, 2024) and Taiwan (Koon Lin et al., 2025).

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Two studies (12.5%) originated from Turkey (Kaya et al., 2025; Uyanık, 2025). Two studies (12.5%) were conducted in Mexico (Palomino-Gamez et al., 2025; Vázquez-Parra et al., 2025). Two studies (12.5%) came from the United States (Nguyen et al., 2025; Sun & Hsiao, 2025). Europe contributed two studies (12.5%): a multinational case study across Spain, Austria, and the USA (Tabuenca et al., 2024) and a collaboration between Italy and Spain (Tumedei et al., 2025). Israel (Sachyani & Gal, 2025) and the Philippines (Santiago, 2025) each contributed one study (6.3%).

Figure 5
Geographical Distribution of Included Studies



The most significant gap in the distribution was its inverse relationship with environmental vulnerability. The regions least represented in the research, including Sub-Saharan Africa, South Asia, Central America, and Oceania, were among the communities most exposed to climate-related risks. This created a structural divide: the communities that need environmental education innovation the most have the least presence in shaping it.

Contributions from Latin America and the Mediterranean were notable for their distinctive place-based approaches. Both studies in Mexico focused on the Santiago River, one of the country's most polluted bodies of water. Tumedei et al. (2025) based their design on the Mar Menor, a Ramsar-listed wetland that became the first ecosystem in Europe to be granted legal personality in September 2022. Sachyani and Gal (2025) grounded their interventions in the conservation of Lesser Kestrels (Falco naumanni) in northern Israel. These five place-based studies (31.3%) demonstrated that local ecological significance and advanced artificial intelligence can coexist and reinforce one another, offering a viable model that can be meaningfully expanded to underrepresented regions.

Discussion

This scoping review studied 16 empirical studies on the use of AI in environmental education published between 2022 and 2025. The findings reveal a rapidly growing yet still immature field characterized by significant diversity across geographical, methodological, instrumental, and theoretical dimensions. The findings presented in this section are interpreted in light of the relevant literature and compared with the findings of other researchers.

The set of 16 studies included in the review represents a small but growing body of evidence. Koseoglu and Erten (2026) also observed a similar trend and reported a marked increase in publications in this field beginning in 2023. The findings of this review confirm this trend. However, the increase in publication volume has not yet been accompanied by methodological consistency or theoretical convergence. The studies exhibited significant variations in terms of research design, AI tool types, theoretical frameworks, and target outputs. This diversity reflects the exploratory nature of the field's early developmental stage.

The findings of this review reveal that LLMs hold a dominant position among AI tools used in environmental education. ChatGPT and the GPT family were used in 10 out of 16 studies. This dominance can be partly explained by practical factors. No additional hardware is required to use these tools. Their costs are low. Teachers can incorpo-

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rate these tools into their lessons without undergoing extensive technical training. Rahman and Watanobe (2023) and ElSayary (2024) observed a similar trend in the broader educational AI literature. Ease of access appears to be the primary driver of adoption.

However, reliance on a single technological ecosystem also brings certain risks. Among the studies examined, there is no research directly comparing GPT family tools with other LLMs. Yang (2025) is the only researcher using KIMI in the study. Chang and Kidman (2023) have noted that information provided by AI in environmental education should not be accepted uncritically. Nevertheless, most of the reviewed studies (Lo, 2023; Montenegro-Rueda et al., 2023) have treated ChatGPT as a useful tool and have not questioned its ecological or epistemological limitations. The field's premature alignment with a single technological ecosystem without sufficient comparative evaluation is considered a cause for concern.

A more advanced set of studies has moved beyond basic applications. Palomino-Gamez et al. (2025) and Vázquez-Parra et al. (2025) developed Alma de Tezontle, a culturally embedded, specialized GPT model. Nguyen et al. (2025) designed five unique chatbot personas, each representing a different stakeholder perspective. These approaches reflect a qualitatively distinct design logic. In these studies, AI is positioned not as a general information source but as an empathetic interlocutor. This distinction is significant from an educational perspective. The aforementioned advanced studies have demonstrated a design philosophy consistent with this principle.

The knowledge-action gap is a persistent problem that has long plagued environmental education. Kollmuss and Agyeman (2002) demonstrated that possessing knowledge about environmental issues does not reliably lead to environmentally friendly behaviors. Portus et al. (2024) confirmed that interventions based solely on knowledge cannot consistently bridge this gap.

The findings of this review indicate that AI is beginning to be applied as a potential bridge to close this gap. Nine studies explicitly aimed to change attitudes or behaviors. Five studies operationalized eco-friendly behavior as the primary outcome variable. This represents a significant shift. Previous AI and education literature has primarily focused on knowledge acquisition and academic achievement.

The AIGB model developed by Wang et al. (2025) provides a theory-based framework to explain how AI use facilitated by teachers influences green behavior. This model identifies psychological factors, educational variables, and technology use as interactive determinants.

Narrative-based AI interventions have produced particularly promising results for emotional change. Palomino-Gamez et al. (2025) reported significant changes in environmental beliefs and behavioral intentions following a single session with Alma de Tezontle. The model utilized empathy and recognition mechanisms as core mechanisms. Vázquez-Parra et al. (2025), however, expanded upon this by targeting structural accountability rather than individual behavior. Students demonstrated a shift from attributing environmental problems to personal preferences toward understanding systemic and institutional causes. This represents a qualitatively different type of learning. It is consistent with the transformative learning theory used as an explanatory framework by Arif et al. (2025).

The studies included in this review reflect a broad spectrum of pedagogical approaches. Content creation and personalized learning emerged as the most common approaches. However, more distinctive models have also emerged. Narrative and empathy development, gamification, and multimodal creative production have emerged as distinct strategies without clear counterparts in other educational fields. Tumedei et al. (2025) designed an interactive system in which children speak directly to the Mar Menor lagoon as first-person narrators. Humanizing an ecosystem in this way is an unconventional yet theoretically grounded choice. Husamah et al. (2025) noted that VR and immersive environments deepen environmental empathy. Narrative-based AI can achieve a similar function at a lower technological cost. This finding is a significant result demonstrating that it is possible to foster emotional connection without requiring advanced technical infrastructure.

Creative transformation is equally noteworthy. Sachyani and Gal (2025) documented that fifth-grade students produced comic books, songs, and box designs over the course of an academic year. Koon Lin et al. (2025) utilized four AI technologies together in a six-week intensive program based on the "Writing is Coding" framework. Students created multimodal environmental narratives using text, images, and video media. Yang (2025) observed that AI image-generation tools accelerate design ideas. Thornhill-Miller et al. (2023) defined creativity and critical thinking as core 21st-century competencies. The studies included in this review demonstrated how AI can facilitate both competencies.

Gamification strategies were employed in three studies. The mechanisms were carefully designed. This created a feedback loop between student behavior and observable environmental data. Strielkowski et al. (2025) found that motivation-designed adaptive AI significantly improved academic outcomes. These studies have demonstrated that motivation and behavioral change can be designed together rather than separately.

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The theoretical foundations varied significantly across the studies examined. One study (Kaya et al., 2025) did not specify any explicit theoretical framework. While a study lacking a theoretical framework can still produce useful descriptive data, it cannot explain why an intervention works and falls short in predicting under what conditions it can be replicated. Similar shortcomings have been identified in systematic reviews on AI in higher education. The remaining 15 studies articulated at least one theoretical or conceptual foundation, indicating that the field, despite its hopeful stage, has shown a relatively strong inclination toward theory-informed research design.

Studies with the most advanced theoretical foundations have produced the richest analytical findings. Nguyen et al. (2025) rigorously applied Value-Sensitive Design across its empirical, conceptual, and technical dimensions. Their tripartite framework directly shaped chatbot features. Wang et al. (2025) developed the AIGB model through a grounded theoretical approach and validated it using structural equation modeling. These approaches demonstrated that theoretical grounding provides explanatory depth.

A geographically shaped variation in theoretical preferences has been observed across the region. Studies centered in the People's Republic of China have shown a tendency to leverage behavioral change and motivation frameworks. Cao and Jian (2024), for instance, grounded their intervention in Environmental Behavior Theory. European and North American studies have predominantly adopted value-driven and ethical design approaches. Latin American studies, however, have emphasized empathy, recognition, and structural accountability. Fu and Weng (2024) identified justice, privacy, and accountability as key principles for responsible AI in K-20 education. The Latin American cluster addressed these principles indirectly through design rather than explicitly naming them. This difference likely reflects distinct research cultures, funding priorities, and differing understandings of the purpose of environmental education. Any initiative aimed at developing a unified theoretical framework for AI in environmental education will need to address these fundamental epistemological differences.

Several theoretical innovations have emerged from this body of work. Wang et al. (2025) proposed the AIGB model. Koon Lin et al. (2025) defined prompt literacy as a unique outcome of environmental education. Santiago (2025) systematically used the IDEE framework to structure AI integration decisions. These contributions are significant. However, they have not yet been tested across multiple environments and have not been integrated into a coherent theoretical framework for this field.

The most significant methodological shortcoming is the near-absence of follow-up measurements. Of the 16 studies reviewed, only one included a delayed post-test. Koon Lin et al. (2025) administered a three-month follow-up assessment, reporting retention rates of 87.3% for technical skills, 92.2% for environmental awareness, 78.4% for cultural sensitivity, and 64.7% for community engagement. While this single longitudinal data point is encouraging, the remaining 15 studies relied exclusively on snapshot measurements taken immediately after the intervention. This is considered a major limitation. The environmental education literature (Liu & Green, 2024; Yang et al, 2022) has demonstrated that lasting behavioral and attitudinal changes require continuous reinforcement over time. Without follow-up data, it is impossible to distinguish between genuine learning and temporary participation effects. This situation is not merely a methodological limitation but also an empirical blind spot with direct implications for policy implementation.

The most common approach for causal claims has been quasi-experimental designs. However, no study has used random assignment. Existing class groups were utilized. This increases the risk of selection bias. Comparisons between experimental and control groups have been weakened. Some studies did not report participant numbers or sampling procedures. This limits the possibilities for replication and meta-analytic synthesis.

Standardized effect sizes were reported in only four of the 16 studies (25%). Cao and Jian (2024) reported R^2 and standardized regression coefficients from mediation analyses. Tumedei et al. (2025) provided Cramér's V (0.86) and r (0.36) for categorical and group comparisons. Koon Lin et al. (2025) reported Cohen's d = 1.11 for pre-post comparisons. Kaya et al. (2025) included partial eta squared in their analytical framework. The remaining 12 studies reported only p-values and descriptive statistics, limiting the possibility of assessing practical significance and conducting future meta-analytic synthesis.

Xiaoyu et al. (2025) identified critical usability flaws in ChatGPT, such as insufficient multimedia support, language barriers, and inadequate accuracy checks. This honest assessment is valuable and rare. Most studies have reported only positive outcomes. Ten records would reduce this bias.

The appropriateness of the intervention has rarely been reported. No clear information has been provided regarding whether teachers adhered to the protocol or whether all planned sessions were conducted. Du et al. (2025) found that enabling conditions, particularly institutional support and technical infrastructure, strongly influence the adoption of AI in environmental education. These conditions were rarely documented in the studies examined.

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Data on intervention intensity also raise important questions regarding feasibility. Koon Lin et al. (2025) required a 72-hour contact period over six weeks. This makes it seem unlikely that the program could serve as a replicable model for widespread curriculum integration. In contrast, single-session designs implemented by Palomino-Gamez et al. (2025) and Vázquez-Parra et al. (2025) reported statistically significant changes in awareness following approximately one to two hours of AI interaction. This suggests that short-term but well-designed exposures can produce measurable short-term effects. The most scalable approaches appear to be those embedded within existing course structures and featuring moderate weekly intensity. The 14-week, two-hour-per-week model implemented by Kaya et al. (2025) exemplifies this balance. However, the long-term effects of all interventions included in this review remain largely unmeasured, with the notable exception of Koon Lin et al.'s (2025) three-month follow-up data.

Seven of the 16 studies originated from East Asia, particularly the P.R. China. This reflects national investment in AI-based education. However, it also indicates that the global evidence base is not distributed evenly across the world. The regions least represented in the research are those most exposed to climate-related risks. Sub-Saharan Africa, South Asia, and Central America are not represented in these studies. This is not merely a research gap. It is also an equity issue. García-López and Trujillo-Linán (2025) argue that digital inequality has shifted from a technical issue to a structural issue of educational justice. Communities most affected by environmental issues have the least access to AI-supported environmental education.

Some studies in the literature have demonstrated the feasibility of culturally embedded AI design. The Alma de Tezontle model is grounded in the ecological and cultural history of the Santiago River basin. Tumedei et al. (2025) based their design on the Mar Menor ecosystem and the life experiences of children in the region. Sachyani and Gal (2025) grounded all their interventions in the conservation of Lesser Kestrels (Falco naumanni) in northern Israel. These examples demonstrate that local significance and advanced artificial intelligence can coexist. They can also reinforce one another. This model can be meaningfully expanded to regions that are underrepresented globally.

AI tools have their own environmental costs. Koseoglu and Erten (2026) noted that a brief conversation with ChatGPT consumes approximately half a liter of water. Billions of queries every day result in a significant total consumption. This is a pedagogical paradox. The tools used to teach environmental sustainability may themselves harm the environment. None of the studies reviewed have explicitly addressed this contradiction.

Chang and Kidman (2023) have expressed concern regarding this. AI that provides ready-made answers may weaken students' ability to conduct independent research. Siemens et al. (2022) addressed this with the Human-Artificial Cognition (HAC) model. They argued that students should produce what AI cannot do, rather than simply copying outputs generated by AI. The studies reviewed demonstrated varying degrees of alignment with this idea. Studies that position students as active creators are more consistent with the HAC model. Studies where AI primarily functions as a content provider are not consistent with this approach.

UNESCO (2022) has defined fairness, transparency, accountability, and privacy as fundamental elements for responsible AI in education. Among the studies reviewed, only Nguyen et al. (2025) systematically addressed these principles through Value-Sensitive Design. Some studies have touched on ethical issues but have not taken action on them. As AI tools become more widespread in environmental education, the importance of having clear ethical guidelines will increase.

Conclusions and Implications

This scoping review has mapped 16 empirical studies on the use of AI in environmental education published between 2022 and 2025. The study was driven by four research questions addressing used AI tools, learning outcomes related to environmental education, methodological characteristics, and geographical distribution. The findings indicated a rapidly growing field that has not yet reached methodological or theoretical maturity.

This review contributes to the literature in several ways. It provides the comprehensive PRISMA-ScR synthesis focusing on AI in environmental education, particularly for the period following the public release of large language models. The five-theme analytical framework developed in this study: cognitive and emotional outcomes, used AI tools and their pedagogical roles, methodological quality, theoretical foundations, and geographic distribution. This can be served as a replicable framework for future reviews as the field expands.

The primary contribution of this review is the identification of three qualitatively distinct design philosophies. In half of the studies, AI was used as a content-enrichment tool. A smaller group, however, has used AI as a personalized learning system with adaptive feedback. The most sophisticated applications have positioned AI as an empathetic and values-driven interlocutor. This typology has not been previously articulated in the literature. It

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provides researchers and practitioners with a clearer vocabulary to define and compare how AI is integrated into environmental education.

The review also reveals that the field is beginning to move beyond mere knowledge transfer. Nine studies explicitly aimed to change attitudes or behaviors. Several of these addressed the knowledge-action gap. To this end, they utilized narrative personalization, empathy-based dialogue, or structural accountability frameworks. This shift is significant because it aligns the use of AI with the fundamental challenge of environmental education: transforming awareness into sustained action. Studies that combine creative production, multimodal design, and student agency have demonstrated the strongest alignment with 21st-century competency frameworks.

The near absence of delayed post-tests represents the most critical methodological gap. Only one study conducted a follow-up assessment. The remaining 15 studies presented their findings based on measurements taken immediately after the intervention. In the absence of longitudinal data, it is impossible to determine whether the reported benefits indicate lasting learning or merely temporary engagement responses. This discrepancy has serious policy implications. Education programs relying solely on evidence of short-term outcomes may overstate the impact of AI-supported interventions.

The geographical concentration of research in East Asia and the overall lack of studies in Sub-Saharan Africa, South Asia, and Central America raise concerns about educational equity. The groups most vulnerable to environmental hazards are the least represented in the development of AI-supported environmental education. Culturally integrated AI designs, including place-based models from Mexico and the Mediterranean, offer a suitable approach for building an evidence base in contexts that are currently underrepresented.

Based on these findings, various priorities can be identified for future research. Longitudinal designs incorporating follow-up assessments at one month, three months, and one year should be established as standard practice. Comparative analyses of several AI tools targeting the same educational goal are essential to transcend the existing dependence on a singular technical framework. Pre-registration of studies will help reduce publication bias. Theoretical integration among behavioral psychology, environmental education theory, and AI design principles remains a long-term need.

For practitioners, the most scalable approaches appear to be those embedded within existing course structures featuring moderate weekly intensity. Intensive programs produce substantial outcomes but necessitate institutional resources that the majority of schools are unable to supply. Policymakers should use the geographical gaps found in this assessment to guide their financing and infrastructural support for research in areas where environmental education is most needed.

Limitations

There are several limitations to consider when interpreting the findings of this review. The evidence base is small. Only 16 studies met the inclusion criteria. Therefore, conclusions about patterns and trends should be considered tentative rather than definitive.

The review includes only English-language publications indexed in Scopus and Web of Science. Research published in Chinese, Spanish, Turkish, Arabic, or other languages was not included. This exclusion may have created a systematic bias, especially considering that P.R. China, Turkey, and Latin American countries actively contribute to the included corpus. Relevant studies conducted in these languages may have been overlooked.

The review covers the period between 2022 and 2025. AI tools have developed rapidly during this period. Studies from 2022 and 2023 were conducted using ChatGPT and other tools in their previous versions. The findings of these studies may not reflect the capabilities of currently available systems.

Grey literature, conference papers, and practitioner reports not indexed in the selected databases were excluded. Therefore, innovative applications documented outside peer-reviewed journals were not included.

Finally, this review is descriptive and synthetic in design. It does not perform a meta-analysis of effect sizes. Quantitative synthesis was not possible due to the heterogeneity of outcomes, measurement tools, and intervention designs across studies. As the evidence base matures, future reviews should attempt meta-analytic synthesis to determine more precise estimates of AI's effects on environmental learning outcomes.

Data Availability Statement

This study is a scoping review of published literature. No new data were collected or generated. All studies included in the review are publicly available through the Scopus and Web of Science databases. The full list of

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included studies is provided in the reference list. The coding scheme and data extraction framework used in this review are available from the corresponding author upon reasonable request.

Ethics Statement

This study did not involve the collection of data from human participants. It is based entirely on the analysis of previously published peer-reviewed studies. Ethical approval was therefore not required. All cited studies were treated in accordance with academic integrity standards. Sources are accurately represented and fully referenced.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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