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Artificial intelligence in science education for SDG 4: A systematic review of AI interventions for ESD and 21st-century competencies

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Abstract
Artificial intelligence (AI) is transforming science education and creating new opportunities to advance education for sustainable development. This systematic literature review followed the preferred reporting items for systematic review 2020 guidelines to examine 43 empirical studies published in prominent journals between January 2020 and July 2026. Studies were synthesized using descriptive and thematic analyses. Publications increased markedly, with 76.7% appearing during 2024-2025. Quantitative approaches predominated (51.2%), followed by mixed methods (23.3%), qualitative (18.6%), and research and development (7.0%). AI interventions included generative AI, AI-augmented instructional design, AI-supported assessment, immersive environments, adaptive learning systems, and AIoT, supporting critical thinking, scientific reasoning, systems thinking, collaboration, AI literacy, and sustainability awareness. Despite challenges related to equitable access, teacher readiness, and ethical implementation, AI demonstrates strong potential to enhance sustainability-oriented science education. These findings highlight current research trends, methodological gaps, and future directions for AI-enabled science education aligned with sustainable development goal 4.

Keywords: artificial intelligence, education for sustainable development, systems thinking, sustainability competencies, systematic literature review

INTRODUCTION

The advancement of digital technology has drastically transformed the way people live, work, and learn. In the context of education, mainly since the emergence of the Industrial Revolution 4.0, both challenges and opportunities have arisen to transform learning approaches to be more relevant to the demands of the times (de Souza et al., 2024). Industry 4.0 refers to the integration of advanced digital technologies, including artificial intelligence (AI), the Internet of things (IoT), big data, cloud computing, and automation, to create intelligent and interconnected systems across industrial and educational sectors. In education, these technologies enable more personalized, data-driven, and technology-enhanced learning environments (Khan et al., 2025). One of the most prominent technologies driving this transformation is AI. AI is no longer a futuristic concept—it has become part of daily life, including in the field of education. This technology holds significant potential to address various learning challenges, particularly in science education, such as the limitations of personalization, learning monitoring, and the development of critical thinking and problem-solving skills (Erduran & Levrini, 2024; Lee et al., 2025).

The rapid development of AI is also closely linked to the emergence of the Society 5.0 concept, which extends the technological advances of Industry 4.0 by emphasizing human well-being. Introduced by the Japanese government in 2016, Society 5.0 was proposed

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Contribution to the literature

- This study provides a systematic synthesis of AI interventions in science education through the lens of education for sustainable development (ESD) and SDG 4. It advances the field by mapping AI intervention types to targeted sustainability competencies and identifying global, methodological, and pedagogical trends.
- The review further proposes the AI-ESD pedagogical alignment framework (APAF), offering a conceptual model that explains how alignment between AI affordances, pedagogical functions, and ESD competencies shapes learning outcomes.
- By highlighting uneven geographical distribution, dominant research designs, and gaps in discipline-specific science integration, this study offers a structured agenda for future research and curriculum development.

to address societal challenges, including population aging, declining birth rates, economic instability, and the increasing frequency of natural disasters. Within this vision, technologies such as AI and the IoT are applied not only to improve industrial efficiency but also to enhance quality of life and promote sustainable development (Rathi et al., 2025). Thus, Society 5.0 positions humans at the center of technological innovation, viewing digital technologies as tools for creating a more inclusive, resilient, and sustainable society.

According to Ali et al. (2024) and Venter et al. (2025), the application of AI in learning activities has the potential to be a breakthrough, improving the effectiveness of learning processes. However, the use of such technology must be approached cautiously to avoid unintended negative consequences, particularly in educational settings. In science education, AI offers excellent opportunities, for instance, by presenting complex concepts through engaging visualizations and simulations. Nonetheless, the presence of teachers remains essential as facilitators who guide and ensure students' comprehensive understanding of the material. Therefore, AI should be regarded as a supporting tool that enriches the learning process, rather than as a complete substitute for the teacher's role. This phenomenon positions AI as a catalyst for a paradigm shift in education, enabling more adaptive, efficient, and inclusive learning systems.

The United Nations' 2030 agenda for sustainable development includes sustainable development goal 4 (SDG 4), which aims to ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. This goal emphasizes not only universal access to education but also the provision of high-quality learning experiences throughout the lifespan. SDG 4 recognizes the transformative role of education in eradicating poverty, advancing gender equality, fostering economic growth, and building peaceful and sustainable societies. Beyond expanding access, it prioritizes improving learning outcomes, enhancing overall educational quality, and strengthening the capacity of education systems to adapt to evolving societal needs (UNESCO, 2024).

The impact of AI on education has received increasing attention because it has the potential to change the way people learn (AlSagri & Sohail, 2024; Pachava et al., 2024), meet the needs of different learners, and support new ways of teaching. The use of AI in education is likely to create more learning opportunities and make teaching more effective (Karim et al., 2026; UNESCO, 2024). However, the incorporation of AI also poses significant challenges, including equity, data privacy, and the future of employment (Karthikeyan & Divayanshu, 2024). Therefore, in order to maximize the role of AI in achieving SDG 4, a balance must be found between these opportunities and risks. To ensure that AI truly helps everyone access inclusive and equitable high-quality education, it needs to be implemented in a thoughtful, ethical, and inclusive manner.

One of the primary challenges in science education is the complexity of the subject matter, which is often abstract and difficult for students to comprehend. Concepts such as atomic structure, ecosystems, or physical laws require not only theoretical but also practical and applicable learning approaches (Anto et al., 2023; Salame et al., 2025; Wang et al., 2024). Therefore, mastering these concepts is crucial for shaping students' scientific awareness of sustainability issues such as climate change, natural resource management, and ecosystem balance. Science education that lacks contextualization often fails to inculcate the values of sustainability essential to life in the 21st-century. On the other hand, time constraints and limited resources in the learning process frequently hinder teachers from implementing innovative approaches that link science with social and environmental realities. In this context, AI presents significant potential to support science education by making it not only interactive, personalized, and adaptive, but also contextual and aligned with the goals of sustainable development (Almasri et al., 2024; Zhang & Leong, 2026). AI offers a range of advanced features in the learning process, including virtual simulations, real-time data analysis, and virtual tutors that provide instant feedback to students. For instance, AI-powered simulations enable students to explore scientific phenomena, such as planetary motion, chemical reactions, or energy flows in ecosystems, in a visually and interactively engaging manner (Gao et al., 2025; Strielkowski et al., 2024; Zhang et al., 2026). This approach enables students to grasp complex scientific concepts more effectively and in a meaningful way. Furthermore, AI supports teachers in designing personalized instructional materials, making learning more efficient, inclusive, and learner-centered.

The integration of AI in science education creates opportunities to cultivate competencies closely aligned with the goals of sustainable development. The findings of Holmes et al. (2019) showed that the use of AI can improve student learning outcomes by up to 20% compared to conventional methods. In countries such as Finland, the United States, and Singapore, AI has been employed in science education not only to deliver content more dynamically but also to foster essential 21st-century skills, including critical thinking, creativity, collaboration, and problem-solving, core competencies needed to address global sustainability challenges (Anselmo et al., 2025; Naseri & Abdullah, 2025). Thus, AI in education functions not merely as a technological tool but as a strategic means to shape a generation of learners who are environmentally conscious, resilient, and responsible for the future of our planet.

Although recent studies have increasingly examined the integration of AI in education in relation to sustainability and the SDGs, important gaps remain. For instance, Apata et al. (2025) examined the contribution of AI in higher education toward achieving SDG 4 and SDG 10, but their review was largely limited to higher education contexts and did not examine how AI interventions support sustainability competencies in science education across different educational levels. Similarly, Filho et al. (2025) synthesized international evidence on AI in sustainability education through multiple case studies, emphasizing personalized learning, engagement, and problem-solving. However, the study adopted a broad sustainability perspective and provided limited analysis of pedagogical approaches, methodological trends, and science-specific learning outcomes. Likewise, Abulibdeh (2025) conducted a systematic and bibliometric review of AI in sustainable education, identifying research trends, ethical issues, and technological applications. Nevertheless, the review primarily mapped publication patterns and thematic developments rather than examining how different AI interventions influence sustainability competencies, instructional practices, and learning outcomes within science education. Consequently, existing reviews provide limited evidence regarding the pedagogical characteristics, methodological approaches, educational contexts, and competency outcomes of AI-supported science education for sustainability.

However, despite these valuable contributions, existing reviews tend to focus either on general AI applications in education, sustainability education broadly, or higher education contexts without specifically analyzing how AI is pedagogically implemented within science learning environments to foster sustainability-oriented competencies. Science education possesses unique characteristics, such as inquiry-based learning, scientific reasoning, and evidence-based argumentation, which require distinct instructional strategies when integrating AI technologies. To date, a comprehensive synthesis systematically examining research trends, instructional approaches, targeted competencies, educational levels, and geographical distribution of AI-supported science learning for sustainability remains limited.

Therefore, this study aims to bridge this gap by providing a systematic literature review (SLR) that specifically investigates the implementation of AI within science education contexts to support sustainability-related competencies, including critical thinking, systems thinking, and sustainability awareness. By focusing on science learning as a distinct disciplinary context, this study offers a more integrated understanding of how AI contributes to sustainability-oriented educational outcomes across diverse learning environments and educational levels.

This study employs a transparent and replicable SLR to provide a comprehensive overview of the role of AI in science education for sustainability. By systematically synthesizing existing studies, this review identifies dominant research patterns, methodological tendencies, pedagogical approaches, and research gaps related to AI-enhanced science learning aligned with the ESD. The findings are expected to serve as an evidence-based reference for researchers, educators, and policymakers, while also supporting the advancement of sustainability-oriented science education within the framework of ESD. Based on this rationale, the present study seeks to address the following research questions:

1. What are the overarching publication trends and geographical distributions in the research of AI in science education for sustainability?
2. What methodological trends and research approaches characterize current studies in this field?
3. Within which pedagogical settings is AI-supported science education for sustainability most frequently implemented?
4. How do AI interventions map ESD learning outcomes and the development of sustainability competencies?

THEORETICAL FOUNDATION

Artificial Intelligence in Science Education

AI has increasingly become an influential technology in transforming science education by enabling adaptive, personalized, and data-driven learning environments. AI technologies such as intelligent tutoring systems, generative AI, learning analytics, and automated assessment tools provide opportunities to enhance students' conceptual understanding and engagement in science learning (Darayseh, 2023; Jia et al., 2024; UNESCO, 2021). AI allows science instruction to move beyond traditional teacher-centered approaches toward more student-centered and inquiry-oriented learning experiences.

Previous studies indicate that AI can support complex scientific learning through visualization, simulation, and real-time feedback mechanisms, which help students better understand abstract scientific concepts. For example, AI-based simulations allow learners to explore scientific phenomena that are difficult to observe directly, such as climate systems, molecular interactions, or energy transformations (Gao et al., 2025). Additionally, AI can assist teachers in monitoring student progress and tailoring instruction based on individual learning needs, thereby improving learning effectiveness and accessibility.

However, despite these advantages, AI also introduces important pedagogical and ethical challenges. Excessive reliance on AI-generated content may reduce students' independent reasoning, critical evaluation, and problem-solving abilities (Bahrini et al., 2023; Hinss et al., 2022). Furthermore, concerns regarding algorithmic bias, data privacy, academic integrity, and unequal access continue to shape discussions on the responsible use of AI in education (Ali et al., 2024; Ward et al., 2024). For teachers, AI supports instructional planning, assessment, and learning analytics, yet it also requires AI literacy and ethical competence to critically evaluate AI-generated outputs.

Beyond its technological capabilities, AI should be understood as a pedagogical enabler rather than merely a digital tool. Its educational value depends on how AI is integrated into learning design, instructional strategies, and assessment practices to support meaningful learning processes (Zawacki-Richter et al., 2019). Consequently, evaluating AI in education requires attention not only to technological innovation but also to its contribution to broader educational goals, including the development of competencies needed to address complex sustainability challenges.

Science Education for Sustainability and ESD

One of the most important educational purposes that can be supported through AI-enhanced learning is ESD. ESD promotes the development of knowledge, skills, values, and attitudes that enable learners to understand complex sustainability challenges and participate responsibly in creating more sustainable societies (UNESCO, 2020). Rather than emphasizing knowledge acquisition alone, ESD advocates transformative learning that integrates environmental, social, and economic dimensions of sustainability while fostering learners' capacity for informed and responsible action.

Science education provides a particularly appropriate context for achieving these goals because many sustainability challenges—including climate change, biodiversity loss, renewable energy, pollution, and resource management—are inherently scientific and interdisciplinary. Through scientific inquiry, evidence-based reasoning, and problem-solving, science education equips learners with scientific literacy, systems thinking, and decision-making competencies that are fundamental to addressing socio-scientific issues (Naseri & Abdullah, 2025; OECD, 2023; Segara et al., 2023). Accordingly, sustainability-oriented science education extends beyond conceptual understanding by encouraging learners to critically analyze complex environmental problems and develop responsible solutions.

Recent UNESCO (2020, 2024) frameworks further emphasize that ESD is not solely concerned with knowledge acquisition but also with cultivating transformative competencies, including critical thinking, systems thinking, anticipatory thinking, collaboration, self-awareness, and responsible action (Bianchi et al., 2022. These competencies require learner-centered pedagogies that promote inquiry, reflection, authentic problem-solving, and active participation in addressing sustainability issues. Accordingly, science education provides an appropriate context for integrating AI-supported learning environments that can facilitate these complex cognitive and socio-emotional processes.

Integration of AI in Sustainability-Oriented Science Learning

The integration of AI into sustainability-oriented science education has emerged as a promising approach to bridging technological innovation with sustainability learning outcomes. AI technologies enable the development of immersive and interactive learning environments, including virtual laboratories, augmented reality simulations, AI-assisted inquiry learning platforms, adaptive learning systems, and generative AI tools (Strielkowski et al., 2024). These technologies facilitate experiential learning that allows students to explore environmental systems, sustainability scenarios, and socio-scientific problems in authentic contexts.

Recent research demonstrates that AI-supported science learning can enhance 21st-century competencies aligned with ESD, including critical thinking, digital

Table 1. Boolean search structure used in the literature retrieval process

Search component	Keywords/terms
AI technology	"Artificial intelligence" OR "Machine learning" OR "Generative AI"
Educational context	"Science education" OR "Science learning" OR "STEM education" OR "Science teaching"
Sustainability context	Sustainability OR "Education for Sustainable Development" OR ESD
Global framework	SDG* OR SDGs OR "Sustainable Development Goals"
Learning outcome focus	"Learning outcome" OR Competenc*
Implementation context	Intervention* OR Implementation OR Integration OR Application*

literacy, collaboration, sustainability awareness, and scientific reasoning (Abulibdeh, 2025; Bianchi et al., 2022). AI-driven adaptive learning systems also support differentiated instruction, enabling learners from diverse educational backgrounds to engage with sustainability concepts at appropriate levels of complexity. Nevertheless, evidence from recent studies suggests that educational outcomes are influenced not simply by the type of AI technology employed but by the way AI is pedagogically implemented (Holmes et al., 2022; UNESCO, 2021; Zawacki-Richter et al., 2019). Similar AI technologies may produce different learning outcomes depending on whether they function as dialogic scaffolds, adaptive tutors, immersive simulations, assessment tools, or curriculum-integrated learning environments. Thus, pedagogical implementation serves as the critical mechanism linking AI technologies with sustainability competencies.

These perspectives suggest that successful AI-supported sustainability education depends on the alignment between three interrelated dimensions:

(1) the technological affordances provided by AI,

(2) the pedagogical functions through which AI is implemented, and

(3) the sustainability competencies targeted within ESD.

This conceptual relationship provides the theoretical basis for the AI-ESD APAF proposed in this review, which conceptualizes AI integration as a pedagogical alignment process rather than a technology adoption process alone. The framework is developed and discussed based on the synthesis of the reviewed studies presented in the results and discussion section.

METHODOLOGY

Research Design

An SLR is a structured research approach used to systematically identify, evaluate, and synthesize existing studies within a specific research domain. By applying predefined procedures and inclusion criteria, an SLR enables researchers to develop a comprehensive and evidence-based understanding of current knowledge, research trends, and existing gaps (Xiao & Watson, 2019). The primary purpose of an SLR is to critically examine theoretical perspectives, methodological approaches, and empirical findings to produce a balanced scholarly synthesis (Wallace & Wray, 2016). To ensure methodological transparency and reporting quality, this review was conducted and reported in accordance with the preferred reporting items for systematic reviews (PRISMA 2020) guidelines (Page et al., 2021). In this study, the SLR approach was employed to investigate the integration of AI in science education for sustainability, with particular emphasis on AI intervention types, learning outcomes, and their alignment with sustainability dimensions and ESD.

This study followed the PRISMA 2020 framework to systematically identify, screen, assess, and synthesize peer-reviewed articles published between January 2020 and July 2026. The review focused on identifying research patterns, methodological trends, and conceptual gaps in studies related to AI integration in sustainability-oriented science education. Through systematic screening and thematic content analysis, the selected studies were examined based on their AI intervention strategies, educational contexts, targeted learning outcomes, and contributions to sustainability education.

Literature Search Process

The research sample consisted of 43 peer-reviewed articles examining the integration of AI in science education for sustainability, published between January 2020 and July 2026. The articles were retrieved from four major academic databases, including Scopus, Web of Science (WoS), IEEE Xplore, and Google Scholar. To ensure consistency with the research objectives, a structured Boolean search strategy was applied using predefined keywords related to AI, science education, sustainability, learning outcomes, and educational interventions.

The search strategy was designed to ensure that retrieved studies explicitly examined AI implementation in science education and its relationship with sustainability-oriented learning outcomes. The Boolean search structure used in the article retrieval process is presented in **Table 1**.

Review Procedure

The review process consisted of the following stages:

1. **Article selection:** Articles were identified and screened following the PRISMA 2020 guidelines (Page et al., 2021). Records were retrieved from

Table 2. Inclusion and exclusion criteria

No	Category	Inclusion criteria	Exclusion criteria
1	Type of publication	Journal articles	Conference proceedings, books, reports, websites
2	Indexing	Scopus-indexed and/or nationally accredited journals	Non-indexed journals
3	Research focus	AI in science education for sustainability/ESD	Studies unrelated to AI or sustainability
4	Publication year	January 2020-July 2026	Published before 2020
5	Research methods	Quantitative, qualitative, mixed methods	Editorials, opinion papers, and literature reviews
6	Field	Science/STEM education	Non-science education fields
7	Participants	Primary to higher education contexts	Non-educational settings

Scopus, WoS, IEEE Xplore, and Google Scholar using a predefined Boolean search strategy. After duplicate removal and eligibility screening based on the inclusion and exclusion criteria (**Table 2**), 43 empirical studies were retained for the final synthesis.

2. **Coding instrument adaptation:** The researchers adapted the paper classification form (PCF) developed by Kizilaslan et al. (2012) as the primary coding instrument. The PCF includes indicators such as publication year, country, educational level, research approach, AI intervention type, learning outcomes, and sustainability dimensions. Information extracted from each study included publication year, country, educational level, target population (e.g., primary school students, junior high school students, senior high school students, undergraduate students, postgraduate students, pre-service teachers, and in-service teachers), sample characteristics, AI intervention type, learning outcomes, sustainability dimensions, and research methodology.
3. **Quality assessment:** To enhance the methodological rigor of this review, the included studies were appraised using the mixed methods appraisal tool (MMAT) version 2018 (Hong et al., 2018). The MMAT was selected because it enables the evaluation of qualitative, quantitative, and mixed-methods studies within a single framework. Development studies were assessed using criteria adapted from the qualitative domain. Overall, 40 studies were classified as high quality and three as moderate quality, indicating that the synthesized evidence was supported by generally robust methodological quality. Detailed appraisal results are provided in **Appendix A**.
4. **Identification of research patterns:** Patterns were identified across the selected studies, focusing on trends in AI implementation, pedagogical strategies, educational levels, learning outcomes, and sustainability dimensions addressed. These patterns provided insights into how AI is being utilized to support sustainability-oriented science education.
5. **Synthesis to address research questions:** The identified patterns were synthesized to systematically address the research questions of this study. The complete study selection procedure, following the PRISMA 2020 guidelines, is presented in **Figure 1**.

RESULT AND DISCUSSION

Overview of Publication Trends and Geographical Distribution

The distribution of the reviewed studies published between January 2020 and July 2026 is illustrated in **Figure 2**. Overall, research on AI-based science education for sustainability demonstrates a marked upward trajectory over the review period. During the initial phase (2020-2021), only one study was published each year, indicating that the integration of AI into science education for sustainability was still an emerging area of research. Publication output increased modestly in 2022 and 2023, with two studies published annually, reflecting growing but still limited scholarly attention. Early studies primarily explored the feasibility of AI applications, including intelligent tutoring systems and data-driven learning environments, to support science learning and sustainability-related competencies.

Between 2020 and 2023, the literature remained relatively limited, with only six studies published over four years. This low publication volume suggests that the intersection of AI, science education, and sustainability has not yet become a mainstream research focus. Most studies during this period investigated the initial adoption of AI technologies and their potential to enhance scientific learning and emerging sustainability competencies.

A substantial increase in publications was observed in 2024, with 11 studies identified. This sharp rise reflects growing international interest in leveraging AI to strengthen science education for sustainability, particularly in fostering scientific literacy, critical thinking, problem-solving, and competencies associated

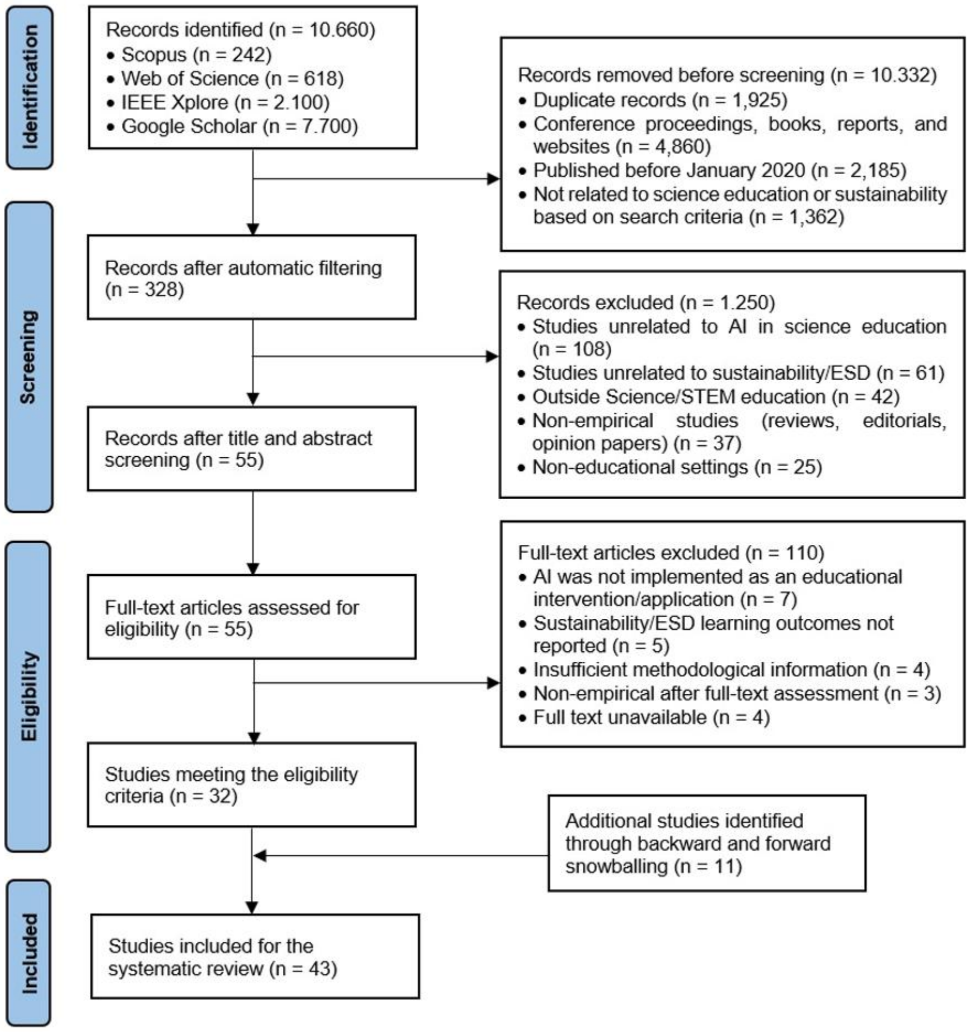

Figure 1. Flowchart of the article selection procedure (Page et al., 2021)

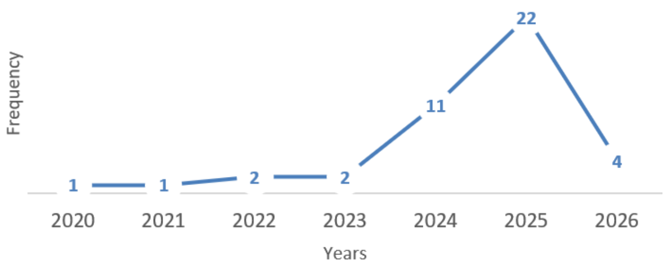

Figure 2. Number of publications per year from January 2020 to July 2026 (the authors' own elaboration)

with ESD. Research during this period increasingly explored AI-supported adaptive learning, generative AI, learning analytics, and immersive technologies to contextualize sustainability issues within science education.

The upward trend accelerated further in 2025, which recorded the highest number of publications (22 studies), accounting for nearly half of all reviewed articles. This remarkable increase indicates that AI-based science education for sustainability has rapidly evolved into a prominent research area. Compared with previous years, studies published in 2025 demonstrated more sophisticated and diverse AI applications, including generative AI, machine learning-based personalization, AI-assisted inquiry learning, intelligent assessment systems, and immersive virtual learning environments. These interventions increasingly targeted not only cognitive outcomes but also higher-order competencies such as systems thinking, sustainability awareness, collaboration, digital literacy, and responsible decision-making.

Although only four studies were identified between January and July 2026, this value should be interpreted with caution because it represents only the first half of the publication year. Nevertheless, the continued publication of empirical studies suggests that scholarly interest remains strong and that research output is likely to increase as additional studies are published during the remainder of 2026.

Overall, the publication trend demonstrates a rapid expansion of research on AI-based science education for sustainability, particularly since 2024. The dramatic growth observed in 2025, together with the continued publication of studies in early 2026, reflects the increasing recognition of AI as a transformative

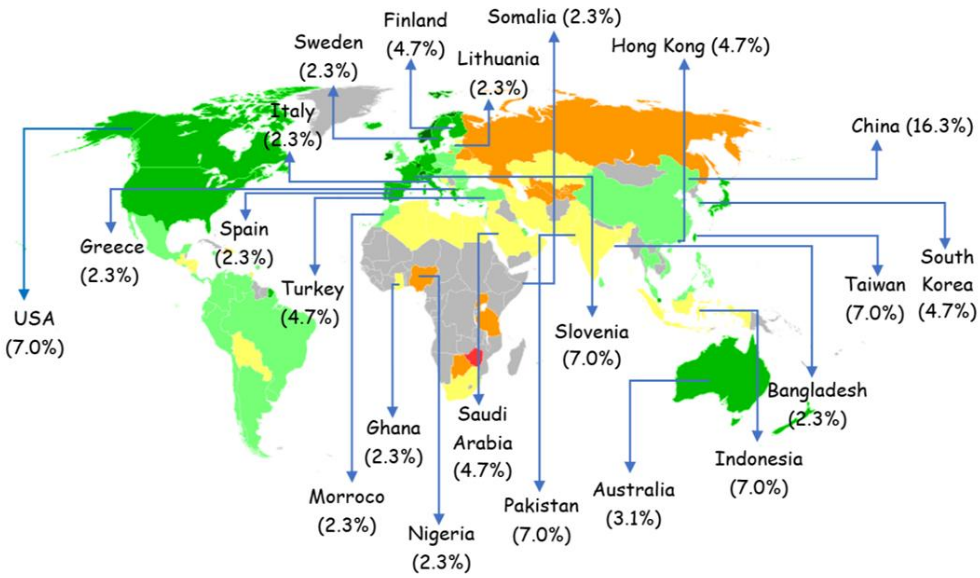

Figure 3. The geographical distribution of studies on AI interventions in science education for sustainable development (the authors' own elaboration)

technology for supporting sustainability-oriented science learning and advancing the objectives of SDG 4 through innovative, learner-centered pedagogical approaches. This trajectory suggests that the field will continue to expand, diversify, and mature in the coming years.

In line with this increasing global interest, the geographical distribution of studies provides further insight into where this research is being developed. The distribution of research on AI in science education for sustainability by country, including frequency (*f*) and percentage (%), is presented in **Figure 3**.

Figure 3 illustrates the global distribution of research on AI in science education for sustainability across different countries. The findings indicate that the reviewed studies are geographically diverse, spanning Asia, Europe, Africa, North America, and Oceania, although the distribution remains uneven across regions.

China contributed the largest share of publications (16.3%; 8 studies). This dominance may reflect the country's long-term national strategy to promote AI research and integrate AI into education, supported by policies encouraging intelligent education and digital transformation (State Council of the People's Republic of China, 2017; UNESCO, 2021). Indonesia, Pakistan, Slovenia, Taiwan, and the United States each contribute 7.0% (3 studies), indicating that these countries have emerged as active contributors to research on AI-supported science education for sustainability. Their growing research output demonstrates increasing efforts to integrate AI technologies into science learning to promote sustainability competencies and 21st-century skills.

A second group of countries, including Finland, Hong Kong, Saudi Arabia, South Korea, and Turkey, each contributes 4.7% (2 studies). These findings suggest sustained scholarly interest in applying AI to science education across diverse educational contexts, with studies focusing on adaptive learning systems, generative AI, immersive technologies, and AI-supported instructional strategies.

The remaining countries—Australia, Bangladesh, Ghana, Greece, Italy, Lithuania, Morocco, Nigeria, Somalia, Spain, and Sweden—each account for 2.3% (1 study). Although individually contributing relatively few studies, collectively they demonstrate the expanding international interest in utilizing AI technologies, such as chatbots, intelligent tutoring systems, learning analytics, and AI-driven assessment tools, to enhance science education and foster sustainability-oriented learning outcomes.

Overall, the distribution suggests that research on AI in science education for sustainability is gaining global momentum but remains concentrated in certain countries with strong technological infrastructure and policy support for AI and education. The relatively lower representation from developing regions highlights opportunities for future research to explore AI-based sustainability education in more diverse socio-economic and educational contexts. Expanding such research could contribute to more inclusive and globally relevant insights into how AI can support sustainable development through science education.

Methodological Trends and Research Approaches

The analysis revealed a wide range of research methods employed in studies on AI-based science education for sustainability and its impacts on learning outcomes and related competencies. Trends in the use of these research methods are summarized in **Table 3**.

Table 3. Methodological landscape of the included studies

Approach	Research methods	Studies	*f*	P (%)
Quantitative	Experimental/quasi-experimental	Koć-Januchta et al. (2020); Jang et al. (2022); Su et al. (2024); Huang and Qiao (2024); Ng et al. (2024); Al-Muqbil (2024); Liu and Château (2025); Pellas (2025)	8	18.6
	Survey/cross-sectional/descriptive	Jeilani and Abubakar (2023); Fošner (2024); Xiao et al. (2025); Zhang et al. (2025); Prosen and Ličen (2025); Ofozobaa et al. (2025); Shah et al. (2026)	7	16.3
	SEM/PLS-SEM/correlational	Cao and Jian (2024); Mutambik (2024); Asad et al. (2025); Cheung and Zhang (2025); Iqbal et al. (2025); Riandi et al. (2026); Iqbal et al. (2026)	7	16.3
Qualitative	Case study/empirical qualitative	Paulauskaite-Taraseviciene et al. (2022); Alamäki et al. (2023); Uğraş et al. (2024); Kim (2025); Charles et al. (2025); Min et al. (2025); Pun et al. (2025); Kim (2026)	8	18.6
Mixed methods	Exploratory/case-based mixed methods	Tabuenca et al. (2024); Savec and Jedrinovic (2025); Capecchi et al. (2025); Tang and Putra (2025); Filho et al. (2025); El Fathi et al. (2025)	6	14.0
	Sequential/embedded mixed methods	Huang et al. (2024); Sultana and Faruk (2024); Kayaalp et al. (2025); Adabor et al. (2025)	4	9.3
R&D	ADDIE/design-based research/development research	Handayani et al. (2021); Hemminki-Reijonen et al. (2025); Sajja et al. (2025)	3	7.0
Total			43	100

Note. P: Percentage

Research on AI-based science education for sustainability is characterized by a diverse range of methodological approaches, with a strong representation of quantitative designs.

As shown in **Table 3**, quantitative studies account for slightly more than half of the reviewed articles, reflecting the dominant use of empirical methods to examine the effectiveness of AI interventions on learning outcomes and related competencies. Among these, experimental and quasi-experimental designs were employed in eight studies (18.6%), such as those conducted by Koć-Januchta et al. (2020), Jang et al. (2022), Su et al. (2024), Huang and Qiao (2024), Ng et al. (2024), Al-Muqbil (2024), Liu and Château (2025), and Pellas (2025). These studies primarily aimed to evaluate causal relationships between AI-supported instructional interventions and outcomes such as learning performance, engagement, critical thinking, scientific inquiry, and sustainability awareness.

In addition, survey-based and cross-sectional descriptive studies constituted the second largest quantitative subgroup, with seven studies (16.3%), including works by Jeilani and Abubakar (2023), Fošner (2024), Xiao et al. (2025), Zhang et al. (2025), Prosen and Ličen (2025), Ofozobaa et al. (2025), and Shah et al. (2026). This approach was mainly used to explore learners' and teachers' perceptions, attitudes toward AI, sustainability literacy, technology acceptance, and self-reported learning outcomes. Furthermore, structural equation modeling (SEM/PLS-SEM) and correlational approaches were applied in seven studies (16.3%), such as those by Cao and Jian (2024), Mutambik (2024), Asad et al. (2025), Cheung and Zhang (2025), Iqbal et al. (2025), Riandi et al. (2026), and Iqbal et al. (2026), to examine complex relationships between AI use, mediating variables, and sustainability-oriented competencies.

Qualitative approaches were also substantially represented, with eight studies (18.6%) adopting case studies or empirical qualitative designs. Studies by Paulauskaite-Taraseviciene et al. (2022), Alamäki et al. (2023), Uğraş et al. (2024), Kim (2025), Charles et al. (2025), Min et al. (2025), Pun et al. (2025), and Kim (2026), for example, provided in-depth insights into how AI-supported learning environments influence students' reasoning, ethical awareness, systems thinking, and sustainability-related learning experiences. These qualitative investigations contributed to a deeper understanding of learning processes and contextual factors that cannot be fully captured through quantitative measures alone.

Moreover, mixed-methods research played a significant role in this body of literature, accounting for ten studies (23.3%). Exploratory and case-based mixed-methods designs were used in six studies (14.0%), including Tabuenca et al. (2024), Savec and Jedrinovic (2025), Capecchi et al. (2025), Tang and Putra (2025), Filho et al. (2025), and El Fathi et al. (2025), to integrate quantitative outcomes with qualitative evidence of learning experiences in AI-enhanced sustainability education. Similarly, sequential or embedded mixed-methods designs were adopted in four studies (9.3%), such as Huang et al. (2024), Sultana and Faruk (2024), Kayaalp et al. (2025), and Adabor et al. (2025), enabling researchers to triangulate learning outcomes, behavioral changes, and student reflections related to sustainability competencies.

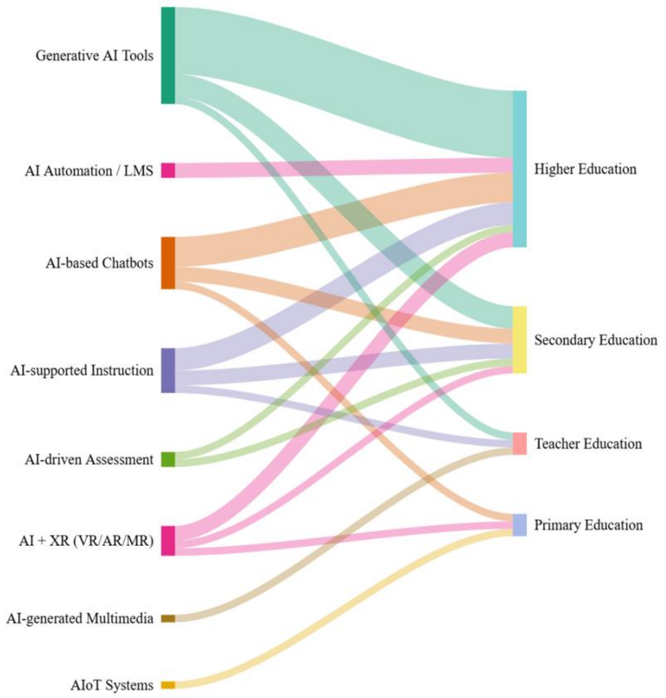

Figure 4. Sankey diagram of the distribution of reviewed studies across educational levels (the authors' own elaboration)

Finally, research and development (R&D) approaches were represented in three studies (7.0%), including Handayani et al. (2021), Hemminki-Reijonen et al. (2025), and Sajja et al. (2025). These studies focused on the design, development, and evaluation of AI-supported instructional materials and learning environments using ADDIE and design-based research methodologies.

Overall, these findings indicate that research on AI-based science education for sustainability relies predominantly on quantitative and mixed-methods approaches, reflecting a strong emphasis on evaluating the immediate effectiveness of AI interventions. However, most quantitative studies employed short-term experimental or quasi-experimental designs conducted over relatively brief instructional periods. While these designs provide evidence of short-term improvements in learning outcomes, they offer limited insight into whether AI interventions produce sustained changes in sustainability awareness, values, or behaviors. Given that ESD aims to foster long-term competencies and responsible action, future research should incorporate longitudinal and follow-up designs to examine the durability of AI-supported learning outcomes over time.

Pedagogical Settings: Educational Levels and Science Disciplines

This analysis illustrates the distribution of selected studies across different educational levels and science disciplines, highlighting how research has been conducted within various educational and pedagogical settings. The flow and proportion of research conducted at each educational stage are visualized using a Sankey diagram, as shown in **Figure 4**.

The Sankey diagram illustrates the distribution of AI-supported science education for sustainability research across different educational levels, revealing a clear concentration at the higher education level. Most of the reviewed studies were conducted with undergraduate and postgraduate students, indicating that higher education institutions serve as the primary context for implementing and evaluating AI-supported interventions for sustainability learning. Studies by Cao and Jian (2024), Fošner (2024), Mutambik (2024), Savec and Jedrinovic (2025), Kim (2025), Xiao et al. (2025), Prosen and Ličen (2025), Alamäki et al. (2023), Jeilani and Abubakar (2023), Sultana and Faruk (2024), and Koć-Januchta et al. (2020) demonstrate extensive use of generative AI tools, AI-based chatbots, AI-supported instructional approaches, and AI automation within learning management systems to foster sustainability awareness, digital literacy, and higher-order thinking among university students and educators. This concentration may reflect the greater availability of digital infrastructure, research funding, institutional autonomy, and AI expertise within universities, making higher education a more accessible environment for piloting emerging AI technologies.

Secondary education represents the second most frequently investigated educational level. Research involving junior and senior high school students, such as Su et al. (2024), Huang and Qiao (2024), Ng et al. (2024), Tang and Putra (2025), Ofozobaa et al. (2025), Pun et al. (2025), and Zhang et al. (2025), highlights the application of generative AI tools, AI-based chatbots, AI-supported instruction, AI-driven assessment, and AI-integrated XR environments. These interventions primarily aimed to improve scientific literacy, inquiry skills, critical thinking, and sustainability-oriented decision-making, reflecting the growing integration of AI into science learning at the secondary level.

Research at the primary education level remains comparatively limited but demonstrates increasing interest. Studies by Tabuenca et al. (2024), Jang et al. (2022), and Uğraş et al. (2024) explored AIoT systems, AI-based chatbots, AI-supported instructional activities, and AI-enhanced XR environments to promote foundational sustainability awareness, digital competence, and systems thinking among younger learners. The relatively small number of studies suggests that AI-supported sustainability education in primary schools is still an emerging area of research. The limited representation of primary education suggests that AI-supported sustainability learning has not yet been widely adapted to younger learners, possibly because of age-appropriate pedagogical considerations, curriculum

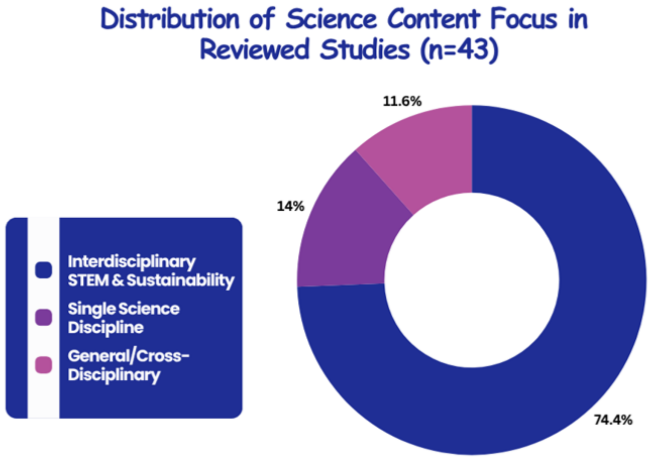

Figure 5. Distribution of research based on the science content (the authors' own elaboration)

constraints, and concerns regarding children's responsible use of AI technologies.

A distinct flow is also observed toward teacher education, encompassing both pre-service and in-service teachers. Studies such as Handayani et al. (2021), Al-Muqbil (2024), Huang et al. (2024), Pellas (2025), Kayaalp et al. (2025), Iqbal et al. (2025), Riandi et al. (2026), and Kim (2026) emphasize the use of generative AI tools, AI-supported instructional programs, and AI-generated multimedia to strengthen AI literacy, pedagogical competence, instructional design, and sustainability-oriented teaching practices. However, most of these studies focused on pre-service teacher preparation, whereas relatively few investigated in-service teachers. This imbalance indicates that the professional development of practicing science teachers in AI-supported sustainability education remains underexplored, despite its importance for large-scale classroom implementation.

Overall, the distribution indicates that AI-supported science education for sustainability is currently dominated by higher education, followed by secondary education, while research in primary and teacher education is expanding but remains comparatively limited. This imbalance highlights an important research gap. Expanding AI-supported sustainability education beyond universities is essential to ensure that AI contributes to sustainability competencies throughout the educational continuum, particularly during foundational schooling and through continuous professional development for practicing teachers. Future research should therefore examine AI implementation across diverse educational levels and evaluate context-specific strategies that support equitable and sustainable adoption.

The analysis further integrates educational levels and science subjects to provide a comprehensive view of how research on AI-supported science education for sustainability is distributed across different pedagogical contexts. The flow and proportion of studies within each science content area are presented using a pie chart, as shown in **Figure 5**.

The distribution of science content in the selected studies indicates that AI integration in sustainability-oriented science education is predominantly situated within interdisciplinary science and STEM contexts. Thirty-two of the 43 reviewed studies (74.4%) adopted interdisciplinary approaches that integrated science with sustainability, technology, engineering, socio-scientific issues, or broader educational contexts. A substantial proportion of these studies focused on environmental and sustainability-related issues, such as climate change, ecosystem conservation, renewable energy, and environmental sustainability, reflecting the strong alignment between science education and ESD. These topics provide authentic, real-world contexts that foster sustainability learning, systems thinking, and interdisciplinary problem-solving (Filho et al., 2019).

In addition, many interdisciplinary studies integrated science education with broader sustainability dimensions, including social, economic, and technological perspectives. This approach aligns with the core principles of ESD, which emphasize interdisciplinary knowledge integration to address complex global challenges (UNESCO, 2020). The incorporation of socio-scientific issues, STEM education, and SDG-oriented learning further strengthens the development of holistic sustainability competencies among learners.

In contrast, only six of the 43 reviewed studies (14.0%) explicitly focused on single science disciplines, primarily biology and physics, within AI-supported learning environments. These studies employed AI-supported tools, problem-based learning, or instructional interventions to enhance conceptual understanding and scientific reasoning in specific subject areas. For instance, Pellas (2025) examined Newtonian mechanics in physics, Ng et al. (2024) investigated force and motion, Tabuenca et al. (2024) explored biological problem-solving in authentic contexts, Al-Muqbil (2024) focused on biology education, Min et al. (2025) examined AI-supported scientific inquiry in physics, and Cheung and Zhang (2025) investigated AI-supported learning related to the Nature of Science. Although discipline-specific applications are evident, they remain less prevalent than interdisciplinary approaches.

Meanwhile, five studies (11.6%) adopted general or cross-disciplinary contexts without focusing on a particular science discipline. These studies primarily explored AI adoption, sustainability education, or pedagogical implementation across broader educational settings rather than within discipline-specific science instruction.

Table 4. Mapping AI intervention types to targeted ESD competencies

AI intervention type	Targeted ESD competencies (SDG 4 context)	*f*	P (%)
Generative AI for learning, dialogue, and content creation	Critical thinking; scientific reasoning; sustainability-oriented decision-making; AI literacy; self-regulated sustainability learning	13	30.2
AI-augmented instructional design for sustainability-oriented learning (AI-based programs/training models)	Sustainability-oriented thinking; conceptual understanding of sustainability systems; collaborative competence	9	20.9
AI adoption, acceptance, and implementation in sustainability education	AI acceptance; technological competence; AI readiness; institutional implementation	8	18.6
AI-supported assessment and learning analytics	Inquiry-based sustainability problem-solving; reflective competence; sustainability reasoning feedback	5	11.6
AI-integrated immersive learning environments (AI + VR/AR/XR)	Systems thinking; environmental awareness; experiential sustainability understanding	4	9.3
Adaptive AI-driven personalized learning systems	Self-regulated learning; differentiated sustainability understanding; critical reasoning	3	7.0
AIoT and intelligent integrated learning systems	Applied problem-solving; environmental systems awareness; data-informed sustainability reasoning	1	2.3
Total		43	100

Note. P: Percentage

Overall, these findings suggest that AI-supported science education for sustainability is predominantly implemented through interdisciplinary STEM contexts, with relatively limited emphasis on discipline-specific science learning. While this trend highlights AI's potential to address complex sustainability challenges through integrated learning, it also reveals opportunities for future research to strengthen AI integration within core science disciplines, such as physics, biology, chemistry, and environmental science.

Core Synthesis: Mapping AI Intervention to ESD Learning Outcomes

Table 4 summarizes the distribution of pedagogically specific AI intervention types and their targeted ESD competencies within SDG 4. Overall, AI is positioned not merely as a technological enhancement but as a pedagogical mechanism intentionally designed to foster sustainability-related competencies. Nevertheless, the uneven frequency across categories indicates that AI-supported ESD remains conceptually fragmented.

The most frequently reported AI intervention was generative AI for learning, dialogue, and content creation (*f* = 13). Generative AI, defined as systems capable of producing new content such as explanations, arguments, feedback, or sustainability scenarios based on learner prompts, was predominantly used as a dialogic scaffold to support learning. Across the reviewed studies, generative AI facilitated scientific reasoning, sustainability-oriented discussions, inquiry, and reflective learning through tools such as ChatGPT and other large language models (Charles et al., 2025; Cheung & Zhang, 2025; El Fathi et al., 2025; Iqbal et al., 2026; Kim, 2026; Liu & Château, 2025; Min et al., 2025; Ng et al., 2024; Pun et al., 2025; Savec & Jedrinovic, 2025; Tang & Putra, 2025; Xiao et al., 2025). The competencies most consistently developed were critical thinking, scientific reasoning, sustainability-oriented decision-making, AI literacy, and self-regulated learning, positioning generative AI as a cognitive partner in ESD rather than merely a content-generation tool.

The second most common intervention was AI-augmented instructional design for sustainability-oriented learning (*f* = 9). This category refers to structured educational programs in which AI is embedded within instructional design and curriculum implementation to cultivate sustainability-oriented thinking, conceptual understanding, and collaborative competence. Rather than functioning as an isolated technological tool, AI was integrated into pedagogical models that supported inquiry, problem solving, and systems thinking in sustainability contexts (Al-Muqbil, 2024; Handayani et al., 2021; Huang & Qiao, 2024; Jang et al., 2022; Kim, 2025; Koć-Januchta et al., 2020; Ofozobaa et al., 2025; Paulauskaite-Taraseviciene et al., 2022; Riandi et al., 2026). This systemic integration closely aligns with SDG 4's emphasis on transformative, learner-centered education.

Another prominent category comprised AI adoption, acceptance, and implementation studies (*f* = 8). Rather than evaluating instructional interventions, these studies investigated factors influencing AI adoption, technological readiness, institutional implementation, and users' perceptions of AI in sustainability-oriented education (Alamäki et al., 2023; Asad et al., 2025; Filho et al., 2025; Fošner, 2024; Iqbal et al., 2025; Mutambik, 2024; Prosen & Ličen, 2025; Shah et al., 2026). Collectively, these studies highlighted that successful AI integration depends not only on technological availability but also on teachers' competencies, institutional support, and learners' acceptance of AI-enhanced educational environments.

AI-supported assessment and learning analytics (f = 5) represented a more evaluative application of AI. In this category, AI was embedded in digital platforms to automate assessment, provide personalized feedback, and analyze students' inquiry performance, thereby strengthening sustainability reasoning and inquiry-based problem-solving (Jeilani & Abubakar, 2023; Mutambik, 2024; Uğraş et al., 2024; Pellas, 2025; Zhang et al., 2025). Although these applications effectively enhanced feedback quality and learning evaluation, their pedagogical role remained primarily supportive rather than transformative.

AI-integrated immersive learning environments (AI + VR/AR/XR) (f = 4) introduced experiential dimensions to sustainability education by combining AI with immersive technologies. Through AI-supported virtual environments and simulations, learners explored dynamic environmental systems and authentic sustainability scenarios, fostering systems thinking, environmental awareness, and engagement in STEM learning (Cao & Jian, 2024; Capecchi et al., 2025; Hemminki-Reijonen et al., 2025; Su et al., 2024).

In contrast, adaptive AI-driven personalized learning systems (f = 3) focus on tailoring learning pathways according to learners' needs by dynamically adjusting instructional content, feedback, and learning progression (Adabor et al., 2025; Sajja et al., 2025); Sultana & Faruk, 2024. These applications primarily supported differentiated instruction, self-regulated learning, and equitable learning opportunities, which are consistent with SDG 4's commitment to inclusive and quality education.

Finally, AI-embedded socio-technical systems (AIoT and integrated intelligent systems) (f = 1) connected classroom learning with real-world environmental data through intelligent sensing technologies, enabling learners to engage in authentic sustainability problem-solving and data-informed decision-making (Tabuenca et al., 2024). Although this application was represented by only one study, it illustrates the potential of AI to bridge classroom instruction with real-world sustainability challenges, highlighting a promising direction for future research.

Although most studies reported positive educational outcomes, evaluations were generally limited to short-term interventions, making it difficult to determine whether sustainability competencies are sustained over time. This highlights the need for longitudinal research to examine lasting behavioral and attitudinal changes central to ESD. Overall, the findings demonstrate that AI interventions support a wide range of ESD competencies. However, the uneven distribution and limited replication of intervention types highlight the need for more integrated, scalable, and longitudinal AI-supported pedagogical designs to advance the objectives of SDG 4 (Advocates for International Development, 2022).

To provide a clearer representation of the relationships between AI intervention types, targeted skills, and learning outcomes, these connections are further visualized in the Sankey diagram presented in **Figure 6**, which illustrates the flow and relative emphasis among intervention categories and educational objectives.

The Sankey diagram visualizes the flow from AI intervention types (layer 1) through pedagogical functions (layer 2) to targeted ESD competencies (layer 3). The dominant pathway originates from generative AI, which primarily serves as a dialogic tool. This pathway supports critical thinking, scientific reasoning, and self-regulated learning, indicating that AI-mediated dialogue fosters metacognitive engagement and higher-order reasoning in sustainability-oriented learning (Charles et al., 2025; Ng et al., 2024; Tang & Putra, 2025). These outcomes align with SDG 4 by emphasizing transformative learning and learner autonomy rather than content delivery alone.

Another prominent flow emerges from AI-augmented instructional design, where AI is embedded within the curriculum to scaffold sustainability thinking, conceptual understanding, and collaboration. This integration illustrates the pedagogical potential of AI in fostering systemic and collaborative ESD competencies, highlighting AI's role in curriculum-level design rather than isolated interventions (Al-Muqbil, 2024; Jang et al., 2022).

AI Adoption and Implementation primarily supports AI readiness, technological competence, and AI acceptance, emphasizing that successful AI integration depends on learners' and educators' preparedness as well as institutional capacity to implement AI effectively in sustainability education (Asad et al., 2025; Iqbal et al., 2025).

Immersive AI environments (VR/AR/XR) channel learners through simulation-based experiences to enhance systems thinking, environmental awareness, and experiential learning. By enabling learners to interact with dynamic sustainability scenarios, these interventions promote experiential and inquiry-driven understanding, complementing the cognitive focus of generative AI (Cao & Jian, 2024; Capecchi et al., 2025; Su et al., 2024).

Flows from AI-supported assessment, adaptive AI, and AIoT systems primarily target feedback, personalization, and real-world integration. Assessment AI strengthens inquiry problem-solving, reflective competence, and sustainability reasoning, adaptive AI fosters personalized learning, differentiated understanding, and critical reasoning, and AIoT facilitates applied problem-solving through authentic sustainability contexts. These pathways underscore the

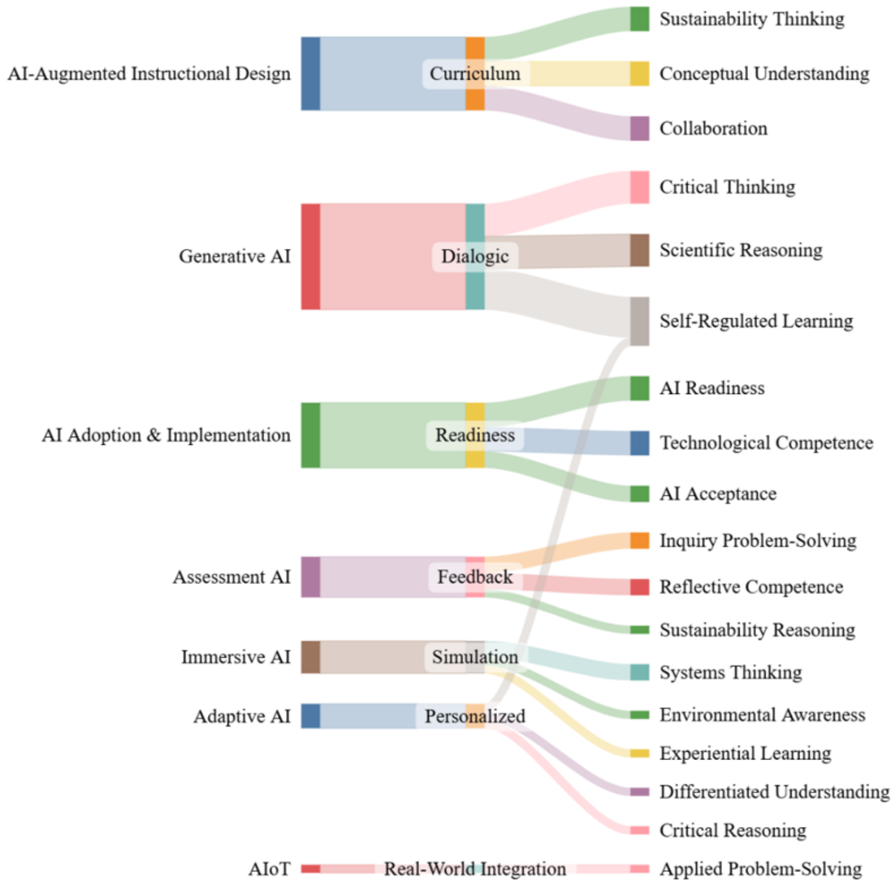

Figure 6. Sankey diagram of interconnections between AI intervention and learning outcomes (the authors' own elaboration)

role of AI in both learning process optimization and real-world sustainability problem-solving (Adabor et al., 2025; Mutambik, 2024; Tabuenca et al., 2024).

Overall, the diagram highlights that the impact of AI in sustainability education is highly contingent on the alignment between AI intervention type, pedagogical implementation, and targeted ESD competencies. Generative AI and immersive simulations primarily support cognitive and experiential outcomes, while assessment, adaptive, implementation-oriented, and AIoT interventions enhance personalization, readiness, and authentic sustainability learning, collectively contributing to the aims of SDG 4.

Toward an AI-ESD Pedagogical Alignment Framework

Building on the synthesis of the reviewed studies, this review proposes the AI-ESD APAF as a conceptual model explaining how AI can support sustainability-oriented science education. Rather than viewing AI as merely a technological innovation, APAF conceptualizes learning outcomes as the result of alignment among technological affordances, pedagogical implementation, and targeted ESD competencies. This proposition addresses a gap identified across the reviewed studies, where AI interventions were frequently evaluated in terms of effectiveness but were rarely conceptualized through an integrated pedagogical perspective (Holmes et al., 2022; UNESCO, 2020; Zawacki-Richter et al., 2019).

Figure 7 presents APAF as a three-layer framework. The Technological Affordance Layer represents the AI intervention types identified in this review, including generative AI, adaptive learning systems, immersive technologies (VR/AR), and AIoT or learning analytics. These technologies provide distinct instructional affordances for supporting learning; however, technology itself does not guarantee meaningful educational outcomes because its effectiveness depends on pedagogical implementation (Holmes et al., 2022; Jia et al., 2024; Zawacki-Richter et al., 2019).

The second layer, Instructional Mediation, represents the pedagogical mechanisms through which AI facilitates learning. According to the reviewed studies, AI functioned as a dialogic scaffold, inquiry-learning facilitator, adaptive feedback provider, and experiential learning environment. Consistent with socio-constructivist and learner-centered perspectives, this layer mediates the relationship between technological capability and learning outcomes by determining how students interact with AI to construct knowledge and solve sustainability-related problems (Gao et al., 2025; Strielkowski et al., 2025; Tang & Putra, 2025; UNESCO, 2024).

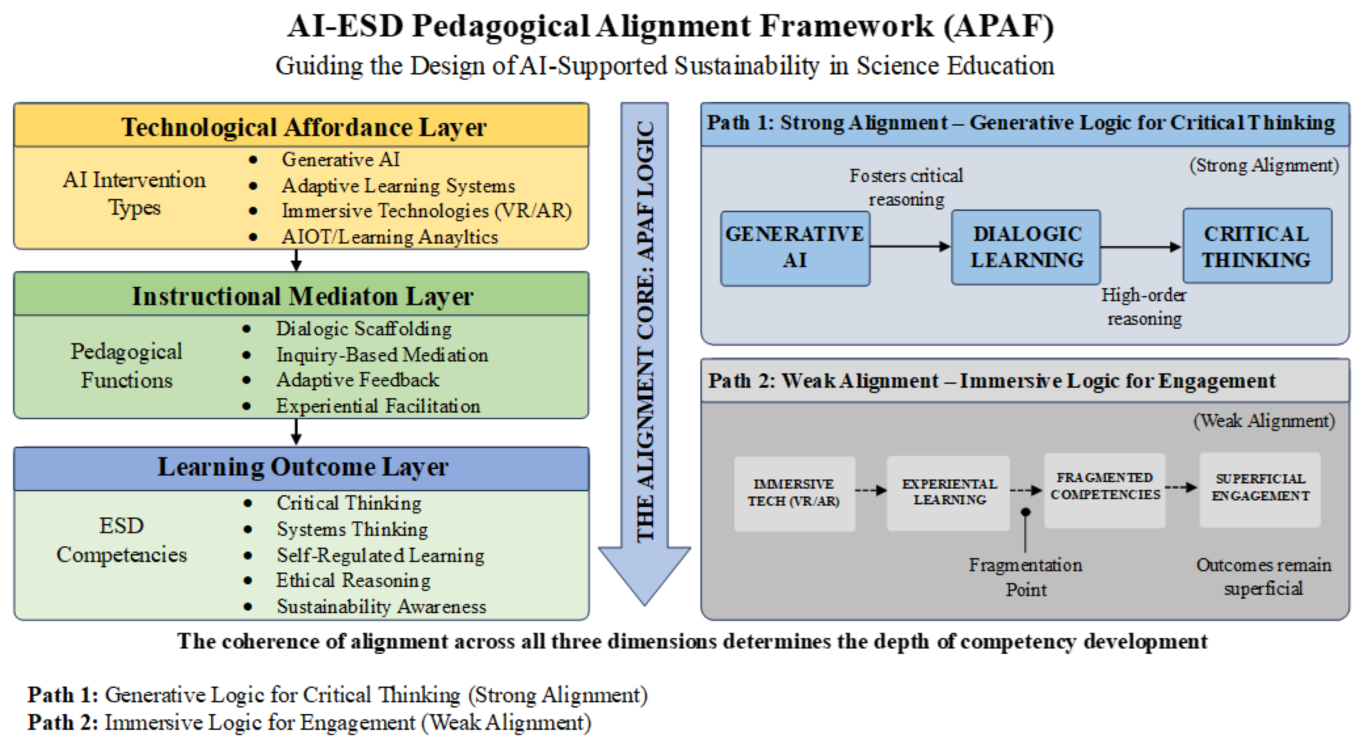

Figure 7. AI-ESD APAF (the authors' own elaboration)

The learning outcome layer comprises the ESD competencies identified throughout this review, including critical thinking, systems thinking, self-regulated learning, ethical reasoning, and sustainability awareness. These competencies reflect the transformative goals of ESD and SDG 4, which emphasize learners' ability to understand complex sustainability challenges, make informed decisions, and act responsibly in diverse contexts (AlSagri & Sohail, 2024; Apata et al., 2025; UNESCO, 2020, 2024).

A central proposition of APAF is the concept of alignment logic, whereby educational outcomes emerge from the coherence between the three layers. As illustrated in Figure 7, strong alignment occurs when AI capabilities are intentionally integrated with appropriate pedagogical strategies to cultivate clearly defined sustainability competencies. For example, the reviewed studies consistently demonstrated that generative AI combined with dialogic learning supported critical thinking, scientific reasoning, and reflective inquiry. Conversely, weak alignment occurs when AI technologies are implemented primarily to enhance engagement without explicit pedagogical integration, resulting in fragmented competencies and relatively superficial learning outcomes. This distinction explains why similar AI technologies often produced substantially different educational outcomes across the reviewed studies (Iqbal et al., 2025; Lee et al., 2025; Pachava et al., 2025).

Compared with previous frameworks that primarily discuss AI technologies or ESD competencies separately, APAF explicitly integrates technological affordances, pedagogical mediation, and targeted sustainability competencies within a single explanatory model. Consequently, the framework provides both a theoretical lens for future research and a practical guide for educators, curriculum developers, and instructional designers to align AI implementation with the transformative objectives of ESD. Future empirical research is needed to validate APAF across different educational levels and cultural contexts and to examine whether stronger alignment among its three components leads to more sustained development of sustainability competencies (Abulibdeh, 2025; Filho et al., 2025).

CONCLUSION

This SLR demonstrates the rapid growth of research on AI in science education for sustainability between January 2020 and July 2026. The findings reveal that AI interventions—including generative AI, AI-augmented instructional design, AI adoption and implementation initiatives, AI-supported assessment and learning analytics, immersive AI environments (VR/AR/XR), adaptive AI-driven personalized learning systems, and AIoT-based learning systems—have contributed to the development of sustainability-oriented competencies, particularly critical thinking, scientific reasoning, systems thinking, sustainability thinking, collaboration, AI literacy, technological competence, self-regulated learning, and sustainability awareness. Quantitative approaches predominated, while qualitative and mixed-methods studies provided complementary insights into learners' experiences, pedagogical processes, and instructional implementation. Research concentrated primarily on higher education and in countries with strong AI and educational research capacity, indicating that AI-supported sustainability education remains unevenly distributed across educational levels and geographical contexts. Nevertheless, current evidence is largely based on short-term intervention studies, highlighting the need for longitudinal research to determine whether AI-supported learning produces lasting sustainability competencies and behavioral change. Overall, the review highlights the growing potential of AI to support transformative science education aligned with the goals of ESD and SDG 4 while identifying important directions for future research and educational practice.

Limitations

This review has several limitations. First, the analysis was limited to 43 peer-reviewed studies indexed in Scopus and published between January 2020 and July 2026, which may have excluded relevant studies indexed in other databases or published as conference proceedings, books, or other forms of scholarly literature. Second, the review employed a descriptive and thematic synthesis rather than a meta-analysis; therefore, the overall magnitude of AI intervention effects could not be quantitatively estimated. Third, although the reviewed studies represented a range of countries, the evidence remained concentrated in higher education settings and a relatively small number of countries, limiting the generalizability of the findings to primary and junior high school as well as underrepresented educational and socio-cultural contexts. Moreover, the evidence synthesized in this review was predominantly derived from short-term intervention studies, limiting conclusions regarding the long-term effectiveness of AI in developing sustainability-related competencies and behaviors.

Future Research

Future research should expand investigations to primary education, vocational education, and underrepresented geographical regions to provide a more comprehensive understanding of AI-supported sustainability education across diverse contexts. Longitudinal, mixed-methods, and design-based research is needed to examine the long-term impact of AI on students' sustainability competencies and learning experiences. In addition, future studies should explore ethical issues—including data privacy, algorithmic bias, equitable access, and academic integrity—to support the responsible implementation of AI in science education. Further research should also investigate how AI can be systematically embedded within curriculum design and teacher professional development to advance the goals of ESD and SDG 4.

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AI statement: The authors stated that they used AI tools solely to improve the grammar and clarity of some sentences. Other than that, no generative AI or AI-based tools were used in the writing, analysis, or preparation of this manuscript. All content was developed solely by the authors and they take full responsibility for this manuscript.

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APPENDIX A

Table A1. Methodological quality assessment of included studies using MMAT (version 2018)

No	Study	MMAT category	C1	C2	C3	C4	C5	Overall
1	Koć-Januchta et al. (2020)	Quantitative non-randomized	✓	✓	✓	✓	✓	High
2	Handayani et al. (2021)	Adapted (development)	✓	✓	✓	✓	✗	Moderate
3	Jang et al. (2022)	Quantitative non-randomized	✓	✓	✓	✓	✓	High
4	Paulauskaite-Taraseviciene et al. (2022)	Qualitative	✓	✓	✓	✓	✓	High
5	Alamäki et al. (2023)	Qualitative	✓	✓	✓	✓	✓	High
6	Jeilani and Abubakar (2023)	Quantitative descriptive	✓	✓	✓	✓	✓	High
7	Cao and Jian (2024)	Quantitative descriptive	✓	✓	✓	✓	✓	High
8	Fošner (2024)	Quantitative descriptive	✓	✓	✓	✓	✓	High
9	Mutambik (2024)	Quantitative descriptive	✓	✓	✓	✓	✓	High
10	Su et al. (2024)	Quantitative non-randomized	✓	✓	✓	✓	✓	High
11	Tabuenca et al. (2024)	Mixed methods	✓	✓	✓	✓	✓	High
12	Huang and Qiao (2024)	Quantitative non-randomized	✓	✓	✓	✓	✓	High
13	Ng et al. (2024)	Quantitative non-randomized	✓	✓	✓	✓	✓	High
14	Huang et al. (2024)	Mixed methods	✓	✓	✓	✓	✓	High
15	Uğraş et al. (2024)	Qualitative	✓	✓	✓	✓	✓	High
16	Sultana and Faruk (2024)	Mixed methods	✓	✓	✓	✓	✓	High
17	Al-Muqbil (2024)	Quantitative non-randomized	✓	✓	✓	✗	✓	Moderate
18	Savec and Jedrinovic (2025)	Mixed methods	✓	✓	✓	✓	✓	High
19	Kim (2025)	Qualitative	✓	✓	✓	✓	✓	High
20	Asad et al. (2025)	Quantitative descriptive	✓	✓	✓	✓	✓	High
21	Xiao et al. (2025)	Quantitative descriptive	✓	✓	✓	✓	✓	High
22	Capecchi et al. (2025)	Mixed methods	✓	✓	✓	✓	✓	High
23	Kayaalp et al. (2025)	Mixed methods	✓	✓	✓	✓	✓	High
24	Charles et al. (2025)	Qualitative	✓	✓	✓	✓	✓	High
25	Leal Filho et al. (2025)	Mixed methods	✓	✓	✓	✓	✓	High
26	Adabor et al. (2025)	Mixed methods	✓	✓	✓	✓	✓	High
27	Tang and Putra (2025)	Mixed methods	✓	✓	✓	✓	✓	High
28	Zhang et al. (2025)	Quantitative descriptive	✓	✓	✓	✓	✓	High
29	Pellas (2025)	Quantitative non-randomized	✓	✓	✓	✓	✓	High
30	Iqbal et al. (2025)	Quantitative descriptive	✓	✓	✓	✓	✓	High
31	Prosen and Ličen (2025)	Quantitative descriptive	✓	✓	✓	✓	✓	High
32	Ofozobaa et al. (2025)	Quantitative descriptive	✓	✓	✓	✓	✓	High
33	Hemminki-Reijonen et al. (2025)	Adapted (DBR)	✓	✓	✓	✓	✓	High
34	Pun et al. (2025)	Qualitative	✓	✓	✓	✓	✓	High
35	Liu and Château (2025)	Quantitative non-randomized	✓	✓	✓	✓	✓	High
36	Cheung and Zhang (2025)	Quantitative descriptive	✓	✓	✓	✓	✓	High
37	El Fathi et al. (2025)	Mixed methods	✓	✓	✓	✓	✓	High
38	Min et al. (2025)	Qualitative	✓	✓	✓	✓	✓	High
39	Sajja et al. (2025)	Adapted (DBR)	✓	✓	✓	✓	✓	High
40	Riandi et al. (2026)	Quantitative descriptive	✓	✓	✓	✓	✓	High
41	Kim (2026)	Qualitative	✓	✓	✓	✓	✓	High
42	Shah et al. (2026)	Quantitative descriptive	✓	✓	✓	✗	✓	Moderate
43	Iqbal et al. (2026)	Quantitative descriptive	✓	✓	✓	✓	✓	High

Note. Legend: ✓: Criterion met & ✗: Criterion not fully met & MMAT criteria: C1: Appropriate research questions and study design; C2: Adequate data collection procedures; C3: Appropriate measurements or data sources; C4: Adequate data analysis and interpretation; & C5: Conclusions supported by the reported findings