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Artificial intelligence-driven green education for sustainable development goals: A review

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Abstract

The intersection of environmental education and artificial intelligence signifies a paradigmatical paradigm shift towards attainment of the United Nations Sustainable Development Goals, and specifically in SDG 4 (Quality Education) and SDG 13 (Climate Action). This is despite the fact that despite considerable growths in technology, the traditional methods used to dispense education are challenged by the need to be able to offer scalable, personalized and beneficial green education that will communicate environmental awareness and sustainability practices. With this overall literature review, the PRISMA methodology will be used to use and analyze emerging trends, applications, and innovations in AI-driven green education systematically. The research considers the innovation of machine learning algorithms, natural language processing, computer vision, and intelligent tutoring systems in the context of environmental literacy, climate change education, and sustainability awareness in the different educational settings. With the thorough study of modern literature, this review provides insight into such key uses as adaptive learning systems, ecological simulations providing virtual reality, AI-based calculators of carbon footprint, and automated environmental monitoring systems. The results indicate that the opportunities exist in the personalized sustainability courses, integration of real-time environmental data, and gamification of learning, whereas such aspects as digital equity, algorithm prejudice, and privacy, as well as technological infrastructure in developing countries, are problematic. The review is a synthesis of the AI methods and teaching and learning processes and application in respect to the sustainability concepts that can be put into practical use by ensuring that teachers, policymakers, technologists, and researchers dedicated to enhancing green education with the use of intelligent systems can use it to embrace a sustainable future.

Keywords: Artificial intelligence, Green education, Sustainable development goals, Climate change, Education, Sustainability.

1. Introduction

The new environment-related issues that mankind has never faced as never before in the twenty-first century require radically differentiated approaches to education that would help build ecological awareness, sustainability skills, and climate competencies among all over the board stakeholders [1,2]. In the United Nations Sustainable Development Goals, implemented in 2015, there was an ambitious global structure that focused on all the socio-economic and environmental crises that are closely related, and education has been identified as a pivotal activity towards the attainment of the seventeen goals. In particular, SDG 4 focuses on high-quality education to be provided to everyone, whereas SDG 13 requires no more exertions to arrange immediate action in addressing the issue of climate change and its consequences [2]. The overlap of these objectives highlights the urgent need of the educational philosophy and practice, which incorporates the environmental awareness, sustainable principles, and ecological stewardship in the context of the learning process [3-5]. Green education goes beyond the conventional environmental science programs, and it encourages a comprehensive appreciation of human- nature interactions, sustains the environmentally friendly lifestyles, builds critical thinking of

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ecological problems, and equips a green learner to be an active contributor to environmental transformations [2,6]. Nevertheless, traditional educational paradigms have significant drawbacks with regard to providing a satisfactory green education on the scale and rate that are needed by our planetary crisis [7-9]. Such constraints encompass standardized curricula that do not respond to local environmental contexts, limited personalization to varied learning requirements and cultural backgrounds, lower involvement of real-world environmental information and phenomena, insufficient evaluation of sustainability competencies looking beyond factual knowledge, and resource limitations that do not allow experiential learning to take place in the natural setting.

The unprecedented opportunities of artificial intelligence technologies developing exponentially offer the scope of green education reforming and breaking these barriers [10]. AI is one that has various computer methods that allow a machine to focus on tasks that usually need the human intelligence to perform, such as learning information, identifying trends, decision making, decoding natural language, and responding to new conditions [10,11]. AI technologies help to support personal learning experience, intelligent content delivery, automated evaluation, predictive analytics, and realistic simulation which when properly introduced to educational environments, can radically improve the efficiency, accessibility, and scalability of green education programs [12-14]. Integration of AI in green education exemplifies three compelling dynamics that have emerged as key influencers of the twenty first century society, including the digital transformation of education through technology-sustained learning settings, the urgent need to maintain environmental sustainability via institutional and policy transformation of the sectors, and the maturation of AI applications to allow fancy applications that once persisted in the research laboratory [3,15-17]. This intersection presents a rare opportunity to rethink environmental education in the digital age to use intelligent systems to foster environmental awareness and sustainability skills that can transform people into the Sustainable Development Goals [18-20]. The uses of AI in the field of green education are characterized by a breathtaking variety of innovations and solutions nowadays [21-23]. The intelligent tutoring systems deliver customized learners on the topics of climate science, ecosystems, renewable energy and sustainable practices, and can vary the difficulty of content and the style of delivery to align with the profile of the specific learner [9,24,25]. To predict the effectiveness of learning, knowledge gaps, and suggest specific intervention based on prediction, machine learning algorithms process the interactions between learners to optimize the effect of learning [26-28]. The concept of natural language processing allows the creation of conversational AI agents that answer the environmental questions, allow discussing the sustainability issues and receiving the real-time response on the written tasks concerning the ecological topics [6,29-31]. Computer vision technologies can be used to help identify species in the biodiversity education process, monitor the environment organization using satellite imagery, and facilitate gestures in the virtual reality ecological simulator.

Adaptive leaning software applies AI rules to provide a dynamic and personalized learning experience with a variety of green educational articles, thereby assuring every learner to learn at their ideal rate and develop the knowledge base on which they are already anchored [32,33]. Artificial Intelligence-driven gamification methods generate compelling sustainability contests, carbon footprint minimizing games, and virtual simulations of eco-management that can encourage behavior change using the game mechanics and immediate feedback [34-36]. Virtual and augmented reality applications will be used and complemented by AI-driven procedural generation and intelligent agents by placing the learners in the environment with the actual ecology of the coral reefs to the rainforest, where they can learn more effectively and in new ways they would not have been able to learn through classroom instruction [16,37-40]. AI-driven educational data mining and learning analytics allow unprecedented information about the ways students become environmentally literate, which teaching methods are the most effective ones when working with various learner groups, and how educational experiences can be translated into a sustainable behavior outside of the classroom [41-43]. Predictive models predict the learning outcomes, determine the at-risk students who need more resources and streamline resources used in education programs [44,45]. With the help of recommendation systems, useful environmental contents, activities in learning processes, and practical sustainability projects are proposed, depending on the interests of learners, objectives, and their performance trends [22,30,46-48]. Complex sustainability skills such as systems thinking, morality-based reasoning about environmental issues and design thinking of sustainable solutions have automated assessment tools to identify skilled competencies in those areas.

Instead of applying AI in green education within the framework of formal education, AI-enhanced green education can be applied in the context of lifelong education, community learning, corporate sustainability training, and community awareness campaigns [49-51]. Artificial intelligence-driven mobile learning applications provide small environmental lessons based on a tight adult schedule and different learning backgrounds [52-55]. Social learning systems make use of AI to help learners collaborate with peers in sustainability projects, provide learners with environmental mentors, and create communities of practice around ecological topics [23,56,57]. The intelligent content curation systems feature automated aggregation and filtering of data deluge of information volumes that pervade the internet, so that the learner obtains extant, useful, challenging material that is believable and relevant to their mission [58-61]. The green educational usage of AI has sustainability impacts on a variety of dimensions. Providing green education can help reduce the ecological footprints, contribute to conservation, and encourage climate action, which is beneficial to the environment. Socially, geographical, economic, and cultural environmental illiteracy can be democratized through the availability of AI-enhanced educational technologies, but issues of equity-related digital divides are also a big challenge [62-64]. Green education also builds labour skills in preparation of a sustainable economy, such as renewable energy, circular economies, green buildings, and regenerative agriculture, economically. In pedagogical terms, AI can be used to refine the approaches to education on the evidence basis; it also speeds up the development of teaching strategies with a positive influence on the development of sustainability competencies.

Although the improvement happens, the area of AI-driven green education is confronted with a multitude of challenges that need to be filled with the attention of researchers, practitioners, and policymakers [1,65,66]. The digital divide comprises inequalities in the access to AI -enhanced learning technologies that have the potential to increase education inequality between advantaged and disadvantaged groups [67-69]. Training data and model architectures may be created in a way that generates unequal classification of the problem, and that reasoning associated with sustainability patterns that are culturally inappropriate in any manner. The privacy of data is a challenge because it is necessary to gather and analyze the large amounts of information on learners to perform personalization and analytics [70,71]. Even the environmental footprint of AI systems per se (e.g. energy expenditure to train massively large models and electronic waste of hardware) is filled with sustainability contradictions that should be taken into account carefully. Among pedagogical considerations, there are how to make sure AI is an addition and not a replacement to the human educators, how to preserve the affective and social elements of environmental education, how to prevent the thinking of techno-solutionists that tend to simplify complex socio-ecological issues, and how to balance the screen-based learning with the direct experiences in natural settings [20,72-74]. The issues associated with technology include the creation of culturally responsive AI systems that can respond to different knowledge systems and values, creation of interpretable models that can be cognized and trusted by educators, robustness and reliability of AI systems whether used in educational settings with limited technical support, and seamless integration of AI tools with current educational infrastructures and processes. Studies involving AI-driven green education are still scattered in computer science, education, environmental investigation, and sustainability science and lack interdisciplinary methodical integration and few framework guides advancement and enforcement [75,76]. Little empirical evidence and data regarding learning outcomes, behavioral effects, and long-term outcomes of AI-enhanced green education are available, with the majority of the research on technological feasibility instead of the educational effectiveness and sustainability outcome. There is a underdeveloped theoretical basis of learning sciences, environmental psychology, and human-AI interaction. Ethical theories that meet special considerations as a result of AI implementation in the environmental education sector need more development.

Even the existing literature shows that there are certain gaps in the literature that need to be studied systematically. To begin with, there are yet to be developed comprehensive frameworks within AI techniques, pedagogical methodology, and sustainability concepts, which are limited to green education, and otherwise, literature is generally concerned with isolated use and lacks the overall contextualization. Second, empirical studies showing long-term effects of AI-informed green education on environmental behaviors, attitudes, and competencies are in the direst need, and most of the research studies present short-term knowledge increase or involvement rates. Third, there is little to no evidence comparing different AI methods and process and system designs to the realization of diverse green education goals and student demographics, which prevents the evidence-based choice.

Fourth, there is a lack of studies on equity aspects such as accessibility, cultural responsiveness, and digital inclusion in AI-driven green learning though environmental justice as it is intertwined with educational equity becomes increasingly acknowledged. Fifth, AI educational technologies, in turn, have a low level of sustainability assessment, such as their lifecycle environmental impact and their demand and use of resources. Sixth, the field of interdisciplinary research between technical AI development and educational research, environmental psychology, and sustainability science is still scant and interferes with holistic understanding. Seven, policy framework and model of responsible development and implementation of the AI in green education settings are undeveloped.

To fill these gaps, the given literature review is aimed at the following purposes:

1) To synthetically assemble the existing knowledge regarding AI applications, methods, and systems in green education in settings of various educational functions and sustainability areas.

2) To determine and classify AI-based methods to improve environmental literacy, climate change education, and sustainability competencies.

3) To examine tools, platforms, frameworks and methodologies used in AI-supported green education projects.

4) To investigate obstacles, constraints and threats to AI application in environmental teaching.

5) To trace the sustainability implications, equity, and ethical aspects of green education based on AI.

This study contributes by illuminating global flow governance through a novel method characterized by smart integration and translation. The study brings value to the research community by shedding light on global flow governance in a innovative way of smartness in terms of integration and translation. This review contributes to the scholarship and practice in a number of ways. First, it is the most extensive synthesis of AI application in green education that gives the researcher and practitioner an overview of the present state of the field presented in a holistic manner. Second, it builds a cohesive conceptual framework linking AI capabilities, educational goals, and sustainability results and allows analyzing the various approaches in a systematic manner. Third, it establishes important research gaps and areas of interest to be filled through research to determine future areas of scholarly enquiry. Fourth, it has examined practical implications to educators, educational technologists and policymakers adopting AI-enhanced green education programs. Fifth, it adds to the extended bodies of literature on technology-mediated education, environmental communication, and sustainable development, existing peculiarities at the point of AI, education, and sustainability.

2. Methodology

The presented extensive literature review is done within the frames of the Preferred Reporting Items of Systematic Reviews and Meta-Analyses to guarantee the transparent and systematic analysis of academic literature on AI-driven green education in accordance with the aims of sustainable development. The PRISMA model serves as an excellent method of literature search, screening and selection, and synthesis to increase the accuracy and coverage of review results. To identify recent and upcoming developments that may have future citation opportunities, the search strategy involved a number of academic databases such as Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ERIC and Google Scholar since publications going back to 2018 were considered current and upcoming. The combination of the search terms resulted in three concept clusters, which are AI-related terms (artificial intelligence, machine learning, deep learning, neural networks, natural language processing, computer vision, intelligent systems, adaptive learning), green education terms (environmental education, sustainability education, climate change education, ecological literacy, environmental literacy, green learning, eco-education), and SDG-related terms (sustainable development goals, SDG, climate action, quality education, environmental sustainability). The use of Boolean operators and wildcards covered the whole area and omitted search accuracy.

Inclusion criteria included peer-reviewed journal articles, conference papers, technical reports and high-quality preprints that could be found in the field of AI applications, techniques, or systems in green education, explicitly or implicitly referring to sustainable development goals. Exclusion criteria narrowed down to only articles that contain empirical evidence or less conceptually rigorous material but discuss only traditional forms of education without AI features in them, general AI or education argument without green/sustainability aspects, or older than. The screening was done using PRISMA methods in addition to preliminarily read the title and abstract, assessing potentially relevant publications in full-text and eventually selection based on inclusion criteria. Citation tracking revealed more related literature. According to AI methods, education uses, spheres of sustainability, research methodologies, and theories, thematic analysis classified the selected publications. The synthesis was used to combine results on the themes, uncovering patterns, contradictions, gaps as well as developing trends. Methodological rigor, quality of evidence, and significance of contribution were assessed as quality measures, but it was not conducted formally because of the heterogeneous nature of the included studies that included technical development, educational research and conceptual analysis.

3. Results and Discussion

3.1 Uses of AI in Green Education

The field of AI-promised green education is highly versatile, which manifests itself in various fields, learning experiences, and educational tasks [36,77-79]. It is also in the intelligent tutoring system, which has been one of the more mature application domains where personalized teaching to are given on environmental topics such as simple ecological concepts up to the complex climate science [80-83]. Such systems make content presentation, pace of difficulty increase, and learning preferences responsive to the individual learner, his/her knowledge, and learning preferences, which is far superior to the engagement and retention of knowledge when teaching with static educational materials. Applications of climate change education use AI to bring abstract and complex climatic phenomena to touch and understand, to a variety of learners. Machine learning models represented as interactive simulations can be used to allow students to edit variables that influence global temperature, sea-level rise, and extreme weather patterns and see the results in real-time. NLP systems process the news articles, social media discussion, and policy text on climate change, which helps the students acquire a deeper insight into various viewpoints, detect misinformation, and learn to be a good media consumer. Historical climate predictions trained to generate scenarios have students explore them and build an appreciation of uncertainty, risk, and long-term impacts, which compose the male category of climate literacy.

Education about biodiversity gains immensely in this scenario where computer visions are used to detect the types of species in reliable, data-driven examples of species-only identification using smartphone cameras and make walkade and field courses more valuable fields of learning [84-86]. The students take pictures of plants, animals, or fungi and will be identified immediately with information about its ecology, conservation status, and learning materials [6,87,88]. Those applications will let learners engage with the surroundings in a very personal way, making contributions to citizen science databases, and proving that every action of an individual serves the overall knowledge. Models trained on large datasets of biodiversity have accuracy in identifying even more challenging species as highly skilled experts but are manageable by learners with minimum training experience, democratizing ecological knowledge once only accessible to well-trained experts. Sustainable lifestyle education applies AI-based tools to monitor the personal carbon footprint, the number of resources spent, and ecological effects and offer an individual recommendation on what and how to change. Such applications can use purchasing trends, transportation decisions, diet, and energy consumption and convert the complicated lifecycle reassessments into uncomplicated measurements and practical recommendations. The elements of gamification such as challenges, achievements and social comparisons provide the incentive to continue playing and experiment with behavior. Machine learning algorithms are used to discover what interventions may be most effective in the case of various user profiles to keep refining recommendation strategies to have the greatest effect.

Education on renewable energy uses simulations enhanced by AI for the user to develop and optimize solar, wind, and hydroelectric systems within real-life conditions. The students change the orientation of panels, the settings of turbines and the storing schemes, whereas artificial intelligence (AI) algorithms provide information about energy production, expenses, and ecology on the basis of real weather conditions and technological standards. These applications build technical knowledge as well as systems thinking in terms of energy transitions, grid connecting, and policy concerns. AI-driven Virtual labs remove the need to have costly physical hardware and allow one to explore scenarios that cannot or cannot be attempted in real-life. Gamification of recycling decisions and modeling of materials flows during the process of production-consumption-disposal and visualization of the environmental impact of various waste management patterns are useful AI applications in waste management and circular economy educational processes. Computer vision system gives immediate feedback regarding accuracy of the sorting, and it assists a learner to internalize the recycling rules and rules that differ among the jurisdictions. The optimization algorithms show the impact of design decisions on recyclability, repairability, and material recovery and encourage a mindset of eco-design that can be applied to a variety of products. The educational program on environmental monitoring combines a practical concept of sensor data in real time with satellite imagery and analysis tools online, powered by AI to provide students with opportunities to explore real-life environmental questions on professional scale by using sufficient technologies. The networks of air quality monitoring with machine learning models assist students to learn the sources of the pollution, its pattern of dispersion, and its health effects in their neighborhoods. Applications on water quality analysis assist students in taking one through procedures when testing them; the AI systems detect dangerous patterns or anomalies to be investigated. Through these experiences, scientific inquisitors, data literacy, and environmental awareness are developed at the same time.

Conservation education incorporates the use of AI-based applications that provide the learner with challenges related to wildlife conservation in real-life situations [89-91]. The students use camera trap photos to estimate a population, report individual animals based on pattern recognition, or group behaviors depending on conservation management. The habitat suitability modeling shows the influence of the environment on species distribution meaning that a student can assess the design of conservation areas or estimate the effects of climate change. Addressing these are these applications, which show how data-intensive, analytical today conservation can be and still have emotional attachments to charismatic species. The education based on urban sustainability applies AI-driven urban planning simulations, in which learners recreate neighborhoods, cities, or areas and balance environmental, social, and economic goals. Models relating to machine learning predict the outcomes of land use choices, transportation frameworks, and distribution of green areas, and patterns in densities, to allow investigation of intricate trade-offs that exist in sustainable urban development. Such simulations create the systems thinking the built environmental sustainability and show how individual decisions can add up to form collective results. The AI use in agriculture has the advantage of presenting accuracy in agriculture techniques, regenerative production, and ecological agricultural concepts. Computer vision identification of crop disease aids the student in knowing about the monitoring of the health of plants, and machine learning models will maximize irrigation, fertilization, and pest control based on sensor data and weather predictions. The possibility of experimentation with an actual sustainability approach by using virtual farm management games with real-thinking AI models can allow the financial inclusion of agricultural literacy in the urban learner population. Ocean literacy Programs use AI-modified virtual reality to engage learners in the marine ecosystems of coral reefs, deep sea or other marine environments. Intelligent agents replicate animal behaviors depending on the ecological relationships and procedural generation generates varied sceneries underwater to be explored. These interactive experiences build emotional opportunities to understand the ocean environments and deeply provide a scientific insight to the nature of marine biodiversity, ecosystem services, and conservation issues.

Natural language interfaces allow interaction with guides in that learners ask natural questions and are provided with contextual information as they explore, integrating discovery learning with guided instructions.

3.2 Artificial Intelligence (AI) Techniques and Technologies

Most AI-driven green education systems use machine learning algorithms as their base, which allow systems to derive patterns and make predictions after analyzing data without being programmed [6,92-94]. Supervised learning algorithms learn to predict views of labeled sets of examples by a model to complete classification problems: plant species using photographs, news post sorted by topic, or an estimate of the level of student knowledge based on their patterns of interactions. However, these models are highly accurate on tasks of good definition and that is the core of most education applications, and they require a lot of training data. The discovery of concealed patterns in instructional data without prior labels, student grouping as indicated by learning behaviors, the recognition of widespread fallacious convictions in the factualization of the environment, or a suspicious pattern in the data of environmental sensors that needs revision are cases of unsupervised listening algorithms which are utilized to find the concealed patterns in educational information. Clustering algorithms will cluster similar learners to be differentiated or will cluster thematically related environmental concepts so as to organize their curriculum. Before reducing the dimensionality, there is visualization of the high-dimensional learning data so that the sophisticated analytics of learners can be simplified and made easier to understand.

Reinforcement learning allows AI agents to acquire the best teaching strategies using trial and errors where they are rewarded when their actions increase the learning outcome. Reinforcement learning in green education settings enhances the ordering of content so as to maximise retention of knowledge, modulates challenge alteration in a way that ensures that staying engaged without being frustrated, and timely intervention response to avert development of any knowledge gaps that may become permanent. These algorithms can be continuously improved since they work with a larger number of learners, and they build pedagogical knowledge in model parameters. The neural networks of deep learning are the driving force of more and more advanced applications of green education that demand the processing of high dimensional data including images, text, speech, and sensor streams. Convolutional neural networks are effectively used in any visual task like identifying species using photos, classifying land use using satellite photos, or detecting gestures when using virtual reality education tools. Neural networks and transformers are used as a sequence processor to take sequential data, such as student interaction logs, environmental time series or natural language text, and can be applied to control intelligent tutoring dialogue, predict learning path or score an automated essay on environmental subjects. Even green education NLP technologies allow artificial intelligence systems to perceive, produce, and communicate in human language, develop conversational GUI, automated feedback systems, and content analysis systems. Named entity recognition recognizes environmental concepts, name of species, locations and other entities, domain-specific to text in order to allow automatic indexing of education material or to analyze student text. Sentiment analysis displays emotional reactions towards environmental issues and enables educators to comprehend the aspect of learning that is based on emotions. The text generation is used to develop custom written explanations, practice problems, and summaries customized to the needs of the individual learners. The question answering systems are instant responses to environmental queries which enhance autonomous learning and inquiry. Computer vision technologies allow the AI to process what is seen by the cameras, satellites, and other imaging devices and aid in various green education purposes. Object detection is used to identify objects such as animals, plants, or other elements of a landscape in photos and videos, which are used to identify fields, automatically track learning activities, or analyze nature photographs. Semantic segmentation can label all pixels of the images allowing the extensive analysis of the land cover, the health of vegetation or the distribution of green spaces in the urban areas based on the satellite data. Pose estimation is used to monitor body positions and motions allowing gesture interactive control over virtual environments or evaluation of practical environmental capabilities.

Fig 1: AI Techniques Adoption vs Educational Effectiveness

Scatter plot shows the relationship between adoption rate of various AI techniques in green education (%) and their measured educational effectiveness scores (0-100). Bubble sizes represent implementation cost. The plot reveals that NLP and ML Classification have high adoption (70-75%) with strong effectiveness (78-85), while emerging techniques like Neuroadaptive Systems show lower adoption (15%) but high potential effectiveness (82).

The recommendation systems employ collaborative, content-based, and hybrid filtering methods to recommend useful learning resources, activities or pathways depending on the profile of the learner, his behaviors, and preferences. These systems assist learners to search through sizeable amounts of environmental material and identify resources that are of interest to them, socially significant to their learning requirements and abilities, as well as open them to a variety of views and themes they may otherwise have chosen on their own. Knowledge graphs the graph-based recommendations. These recommendations, which are made based on knowledge graphs, provide semantic links between the environmental concepts and give the learners meaningful conceptual paths to follow. AI generative models generate new content such as text, images, simulation, and learning processes to a particular educational purpose. Mass scale large language models create personalized explanations, examples, practice problems, and feedback, significantly increasing the scale of personalized teaching. The generation models construct visual images of the environmental concepts, the future scenario or abstract ideas and assist in understanding and imagination. The different types of procedural generation algorithm generate a variety of virtual environments, ecosystems, and sustainability challenges which ensure different experiences and keep the interactions interesting in repeated interactions.

Predictive analytics uses statistical modeling and machine learning to predict the performance of students, detect students who are at risk, and predict the requirements of those students. The context of green education, predictive models of green education are used to estimate the probability of meeting learning goals, future levels of engagement, or predict the probability of behavior change depending on the educational intervention used. This has been made possible by early warning systems that alert educators whenever they notice attentiveness or confusion among students so that they can be helped promptly. Environmental phenomena that are being learned by students are also predicted by predictive models and make education significant to actual events. Learning analytics are more inclusive of the data gathering, analysis and presentation of learner patterns, activities, and results. The Dashboards provide teachers with practical information regarding specific students and classroom trends as well as facilitate evidence-based pedagogical actions. Network analysis shows the leadership pattern of a group sustainability project or a learning community knowledge sharing. Process mining rebuilds learning paths based on educational material, whereby effective and ineffective methods are found. These analytics make educational big data useful in enhancing teaching and learning. Multi-agent systems are simulations with complex phenomena of the environment and society by exchanging messages between multiple AI agents who model various actors, species, or elements of the system. Students can see these emergent behaviors that come out of simple rules and gain some knowledge about complexity, feedback loops and system dynamics that form the core of environmental literacy. The agent-based models reveal ecosystem interactions, resource management dilemma, or social diffusion of sustainable practices and bring to reality abstract sustainability ideas.

Complex decision problems that are of interest to environmental education and sustainability are solved using optimization algorithms, which are finding optimal solutions subject to restrictions. Efficient resource allocation, design of a renewable energy system, the choice of the conservation areas, or the design of the sustainable supply chain can be shown by the use of the linear programming and the genetic algorithms and other methods of optimization. Students develop goals, define limitations, analyze solutions and create optimization thinking that can be utilized in sustainability areas. Federated learning and edge computing can assist AI applications deployed on mobile devices and analyze the environment with limited connectivity, which would fix infrastructure issues in the developing world. These distributed methods process images locally, and not requiring connection with the cloud, and this decreases latencies and bandwidth needs and privacy issues. Research Federated learning models are trained on many devices without the necessity to concentrate sensitive learner data and trade personalization and privacy.

3.3 Intelligent Tutoring System and Adaptive Learning.

Intelligent tutoring systems (ITS) are advanced uses of AI in the field of green learning and use tutoring systems to offer personalized learning based on the needs, knowledge, or progress of the learner [6,9,92-94]. Four main elements of these systems include domain models that represent knowledge structures of environment issues, student models that record specific features and knowledge of individual learners, pedagogical models that undertake instruction models and interaction through interface components. Existing advanced ITS on green education go further past all question and answer type format to include rich multimedia content, interactive simulations, teamwork activity and real-life problems solving. The domain modeling of the environmental education has special implication due to the interdisciplinary nature of sustainability issues in the natural sciences, social sciences, economics, ethics and policy. The effective ITS model such knowledge graphs among concepts in different areas that permit learning by exposing the relationships instead of individual facts. Misconception libraries show popular fallacies in environmental thinking like the confusion of weather and climate, the misconception of energy in the ecosystem, or a false simplification of multifaceted socio-ecological interactions. The system is based on the use of such libraries to identify cases of misconceptions among students and give them specific remedial instructions. The components of green education ITS Student modeling follow a variety of dimensions in addition to the factual knowledge such affective state like environmental concern and self-efficacy, behavioral intentions and reported behaviors, skills such as data analysis and systems thinking, and metacognitiveness towards learning processes. Bayesian knowledge tracing and variations on it provide latent knowledge state inferences with observable responses and preserves probability distributions on what students know. Such probabilistic models allow making principled decisions that are under uncertainty of educational assessment. More advanced student prototypes bring on board motivational attributes, learning styles, cultural orientations as well as a background experience that influences the worldviews towards the environment.

The green education ITS that have been applied in pedagogical strategies include direct instruction and inquiry-based learning based on the learning objectives and student needs. Self-explanatory worked examples are also effective because they allow the students to become familiar with the environmental problem-solving processes and build up conceptual knowledge. Scaffolded inquiry is based on an investigation of students to questions about the real environment with gradually less system and more learner responsible. With problem-based learning, there are complicated sustainability issues that need to be brought together with various ideas and factors. The Socratic dialogue systems ask probing questions that elicit misconceptions and bring deeper thinking as opposed to offering proper responses. Adaptive sequencing algorithms identify the best course of learning content development by giving updates on student models. Macro-adaptation and micro-adaptation vary in terms of activities of instruction, topics, or learning tracks being chosen by macro-adaptation and the fine-tuning of details of activities, like hint specificity, feedback timing, or example difficulty. The sequencing of the curriculum allows walking a fine line between development of the requisite skills and at the same time ensures interest by introducing different activities and applications. Multi-armed bandit strategies and other dynamic online learning strategies are utilized in advanced systems that optimize sequencing strategies by constantly running experiments and continually analyzing information. Feedback in green education ITS does not just show whether something is right but will elaborate on the errors and connect it to the point of reasoning as a student in order to achieve a better understanding. Elaborated feedback involves responding to a particular mistake committed and giving some advice on how to do it right, or possibly using an analogy or extra example. By means of Metacognitive feedback, the students are able to take a reflection upon the way they learn and create a self-regulated learning ability that could be used out of the specific material. Affective feedback recognizes emotional reaction to adversarial environmental matters and promotes forbearance.

Several students should be able to collaboratively learn on sustainability issues and the ITS allows efficient interaction of students. Through group formation algorithm, teams are formed having complementary knowledge and skills. The system also pays attention to the level of collaboration by intervening in cases where conversations are not productive or where the dominant students isolate other students. Collaboration scripts: Collaboration scripts are scripts that present systematic patterns of interaction that facilitate knowledge sharing and group thinking. Group discourse is analyzed to discover learning opportunity and evaluate collaborative competencies that are important in sustainability education. The embodied conversational agents are tutors, learning companions or virtual teaching assistants in green learning systems. Such agents use natural language understanding and generation, system coupled with animated avatars with suitable emotional portrayals and gestures. Social dialogue establishes friendly relationships with the pedagogical agents who show interest in environmental issues and who demonstrate models of good attitudes towards sustainability. Engagement and motivation in the social presence of agents increases the effectiveness of younger learners, although care must be taken to avoid stereotyping some cultural aspects and subtly use such agents should they exist. Mobile ITS implement adaptive green education to the smartphones and tablets where learning is inbuilt in the day-to-day lives and outdoor activities. Context-aware features make use of GPS, camera and sensor up to date a user with location-specific information in the environment, field observations or learning opportunities depending on the environment around the student. Augmented reality superimposes any educational material on real-life settings to align the abstract with the real. Mobile ITS should be able to strike a balance between pedagogical expertise and interface simplicity acceptable on small displays and ad hoc attention.

IGTS Game-based integrally incorporate adaptive learning into interactive games, and games inherently provide motivation that ultimately exerts the outcomes of learning. The games on environmental management put the students in the position of balancing the competing goals, but the system regulates the challenge, offers scaffolding and incorporates the learning material into the gaming process without any interruptions. Instructional games generated by narrative adjust the play, depending on students, and build their experiences around learning where the story is the learning component. The stealth method of assessment assumes that the gameplay behavior is used to determine the knowledge of students without the use of explicit testing, to alleviate anxiety among students and keep them engaged.

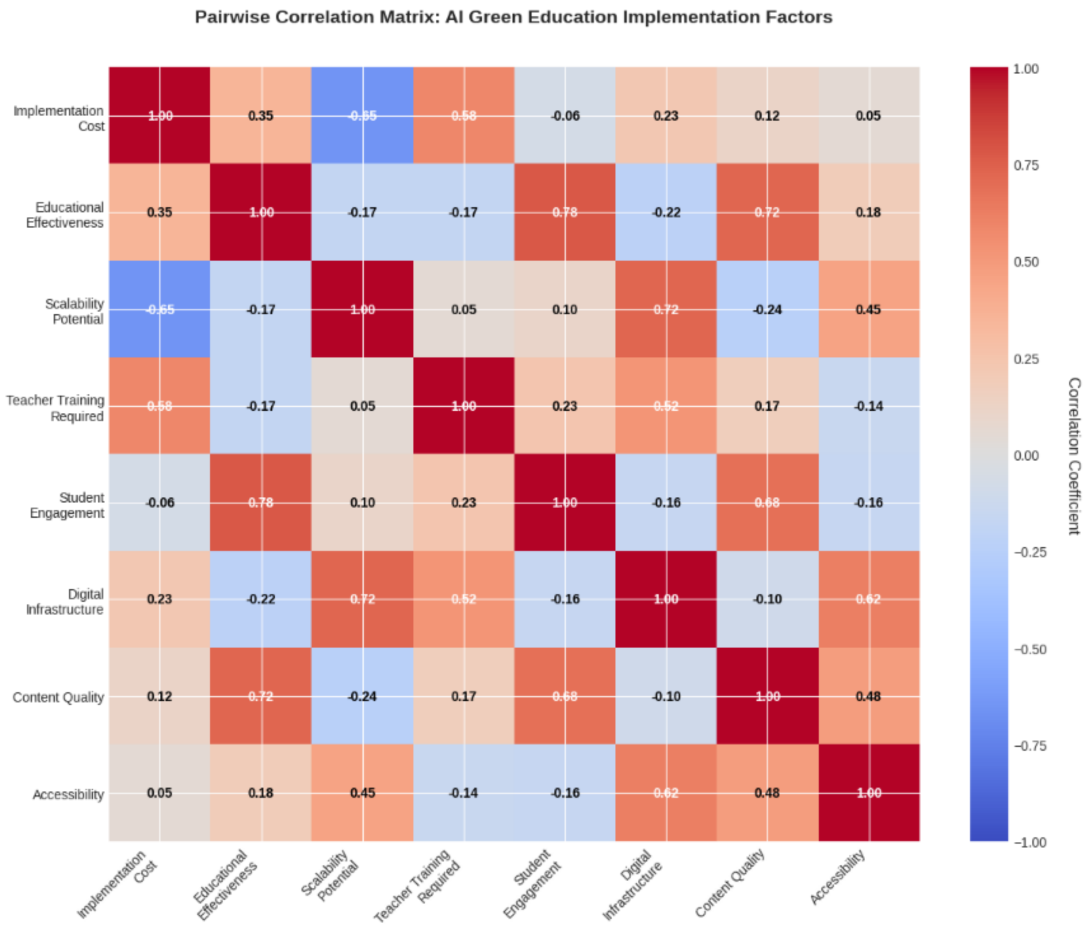

Fig 2: Pairwise Correlation Heatmap - AI Implementation Factors

Fig. 2 shows strong positive correlations between Effectiveness-Engagement (0.78), Infrastructure-Scalability (0.72). Cost negatively correlates with Scalability (-0.65). Teacher Training shows moderate positive correlation with Cost (0.58).

3.4 Green Education of Virtual and Augmented Reality.

AI-enhanced virtual reality (VR) and augmented reality (AR) technologies provide immersive learning, where students are taken to ecosystems, future time and space scales, which cannot be dealt with using usual teaching methods [95-96]. VR worlds create simulators of rain forests, coral reefs, arctic, and other ecosystems that can be viewed, heard, and even felt with visual, auditory, and haptic fidelity to the real world to trigger emotional reaction and haptics learning. Through natural movement and interaction, ecological relationships are studied, change in the environment observed and attitudes of various organisms or other stakeholders in environmental conflicts, studied. Procedural generation AI can generate a variety of distinct and realistic virtual ecosystems with natural variation but in accordance with ecological principles. The terrain, water flows, vegetation distributions, and atmospheric conditions are created using algorithms, which depend on environmental parameters and random seeds, thus each student has unique, but scientifically accurate environments. It is very variant, which does not allow the rote learning and allows revisiting again to explore more. The virtual time of dynamic ecosystems changes through the seasons, through the succession or reactions to disturbances made by students. Virtual agents Intelligence VR environments are filled with intelligent virtual agents that simulate an animal behavior, plant growth, or human actors using an ecological and social science-based AI model. Animal agents are conditionally responsive, relational and responsive to presence of students through proper flight behavior and curiosity as well as appropriate aggression according to the nature of the species. These agents render ecosystem dynamic and vibrant instead of being museums. Learners are also able to view the behaviours of people, follow the individuals through time or participate in virtual ecological studies where environmental variables can be altered and the response of the population can be observed.

The interaction of natural language is possible in VR so that students may ask questions, request information, or talk to decision-making virtual characters in a speech instead of a menu or text input. These interactions are based on AI language models, which give contextually relevant answers without interrupting the process of understanding. Virtual field guides provide name of species that have been found and clarify ecological relationships whenever a student asks a question. The use of conversational agents that represent the stakeholders in environmental scandals would enable the students to realize the various lines of thought via discussions. Gesture and gaze tracking allow people to interact with virtual space in a natural way, as identifying the movement of hands to manipulate virtual objects, study the principles of visual attention changes to determine the involvement or understanding, and adjust slides according to the location of the gaze of students. Embodied interactions such as picking up some virtual plants and looking at them, touching animals or pointing to demand information add to the learning process and memory. Eye-tracking analytics can be used to understand what features of the environment students are paying attention to, what they are actually reading in any explanation, and when they are feeling confused, overloaded.

AR is the superposition of computer-generated data and virtual reality on real things seen through the screens of smart phones or tablets or transparent head mounted I view devices. AR field guides are used to recognize and name plants and animals within the real ecosystems with names, images, descriptions, and conservation status shown when students point devices on organisms. Historical AR makes the historic environmental conditions of the place where they are located recountable thus, letting students observe how the environment has varied over time. The visualization of abstract predictions through Future scenario AR can be a visual representation of possible climate change, sea level increase, or urbanization, and it also makes the impact of predictions emotionally relevant. Collaborative VR provides a common virtual space that can host a group of students, facilitating social learning, work on environmental sustainability issues in teams, and peer teaching. Avatars with the staton of every student make it possible to recognize them and be socially present as they join in virtual ecosystem restoration, start to learn complex environmental systems together, or engage in simulated stakeholder negotiations. The artificial intelligence mediates collaborative tasks, proposing students different activities to complete depending on the area of knowledge and expertise as well as critical information that particular students are likely to overlook and generalizing the findings of the discussion to general knowledge. Multimodal learning analytics extracts detailed behavioral information on VR experiences such as movement, interaction decision-making, verbal and nonverbally spoken words, physiological and attention behaviors. Machine learning is used to analyze such data flows to evaluate engagement, find learning situations, determine misconceptions or misunderstandings, and determine the development of skills. The predictive models serve to predict the results of learning using the behaviors shown at the beginning of the session, to conduct adaptive interventions. Privacy-sensitive analytics combine the behavioral patterns of the users to enhance the design of education VR without infringing the privacy of individuals.

The consideration of accessibility can guarantee that VR and AR green learning can benefit a wider range of academic clients, such as the ones with visual or mobility disabilities or neurological capabilities. Audio descriptions read the information displayed on the screen to the users who are visually impaired whereas spatial audio gives them directions. Comfort features place an end on the motion sickness by using vignetting and teleportation movement, or by seating experiences. Sensory sensitivity accommodations modulate visual intensity, eliminate flashing aspects, or other over-stimulating features of the users with autism or ADHD. Universal design concepts form experiences that can be accessed and is not exceptional in any way. Ecological validity makes the virtual worlds recreate real ecosystems instead of promoting illusions and simplistic beliefs. The development is advised by scientific experts who make sure that species practices, ecosystem processes, and relationships are relevant to the prevailing knowledge. Stylized aesthetics are a balance between realism, performance and clarity without the effects of uncanny valley, but with scientific accuracy. Categorizing speculative future states explicitly means that speculative and present circumstances are very distinct and one can be certain of what is being observed as opposed to what is being predicted.

3.5 Gamification and Serious Games.

Gamification uses the game design components to a green education experience and uses motivational affordances of games to promote more engagement, persistence, and learning [9,95,96]. External motivation in terms of points, badges, leaderboards, challenges, and progress indicators are used to provide excellent recognition of achievement. These components should be designed with caution to facilitate learning goals not to distract the goals instead they should not be begetters of competition that stems out the cooperation or extrinsic rewards that overwhelm the inherent environmental values. The elements of gamification are personalized according to the learners profiles (i.e., social comparison elements are favored by competitive individuals, mastery progression elements by achievement-oriented learners, and narrative elements by story motivated learners). Challenge-based learning introduces students with more and more complex issues in the environment demanding integration and application of knowledge. Different challenges through AI are created according to the situation of the real world and the challenge is adjusted to the needed level so as not to make it easy and frustrating. Scaffolding offers a clue, aids or simplified versions of problems when the students are in difficulties, and the supports are eliminated as competence builds up. Variety of challenges make sure that one is trained to work with a variety of environmental circumstances, magnitude, and methods of solve the problem, as opposed to the widespread use of limited protocols.

Narrative-based learning serves as the implementation of educational material in the form of strong stories that add emotional connection and substantive backgrounds to knowledge implementation [97-99]. Examples of environmental narrative games can be: environmental scientists uncovering suspicious changes in ecosystems, policy advisors under political limitations and working towards a sustainable future, or indigenous people preserving traditional lands against the process of development. Branching stories follow the student decisions and actions to introduce a personalized storyline, that is more related to their values, knowledge, and decisions. AI creates plotlines, dialogue and scenes that react in real time to interactions on the part of a student yet do not sacrifice plot structure or educational goal. Complex environmental systems are simulated by simulation games, which allow experimenting and testing hypothesis as well as forming systems thinking. The simulation games Climate simulation games are simulations that allow students to modify policy parameters, source of energies and pattern of consumption, and see how this affects temperature, sea levels, and extreme weather over the simulated decades. Simulations of ecosystem management find a balance between the populations of species, conservation of a habitat, extraction of resources and human development, and this presentation unfolds trade-offs and unintended consequences. Environmental externalities are included in economic simulations that show how market failures cause the deterioration of the environment and how policy interventions can help to bring the two together (sustainability and economic incentives).

The role-playing games will place students in the role of various stakeholders in various environmental controversies; this will allow them to have empathy, critical thinking of various perspectives and social aspects of sustainability. The role of a student could be that of a corporate executive, environmental activist, indigenous leader, government regulator or a local resident that would be impacted by planned projects. Based on the real-world groups that they represent, AI creates realistic positions, concerns, and limitations of the stakeholders. Mechanics of negotiation and consensus-building necessitate the search of solutions to a variety of views and the resulting creation of collaboration and communication skills, necessary in solving problems of the environment in the real world. Citizen science games allow students to participate in real world data gatherings and analysis that goes into actual scientific studies and in the same time learn how to monitor the environment and ecological concepts. They can be based on the identification of species on photos of camera traps by players, categorizing galaxy shapes to learn about climate-altering astronomical phenomena, or transcribing past weather engraving to broaden climate records. The features of gamification, such as scoring accuracy, new content offered by contribution, and the visualization of the ways individual contribution becomes scientific discoveries, hold motivation. AI enables quality control, marks doubtful classifications so that the latter can be reviewed by an expert, and also presents training that is determined by the performance of the player.

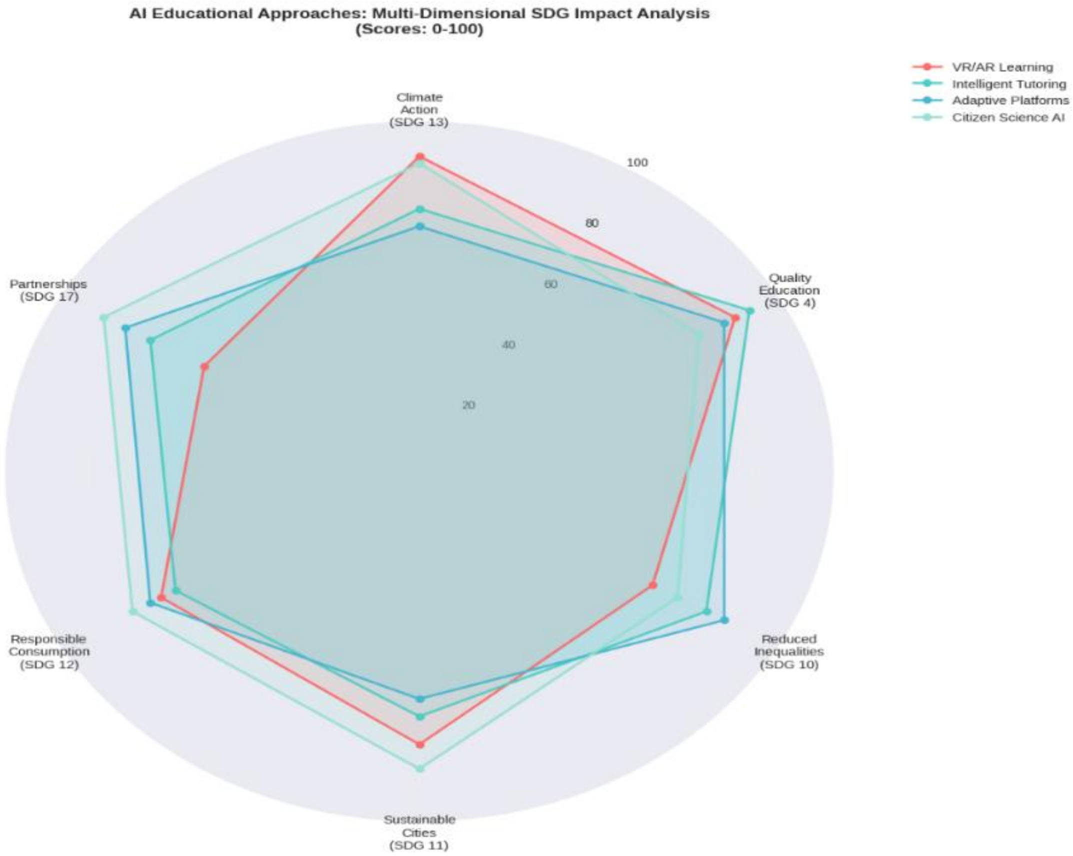

Fig 3: Multi-Dimensional SDG Impact Analysis (Radar Chart)

Fig 3 shows VR/AR Learning excels in Climate Action (90) and Quality Education (88, Intelligent Tutoring leads in Quality Education (92), Adaptive Platforms in Inequalities (85), Citizen Science AI strongest in Partnerships (88) and Climate Action (88).

Behavior change games are focused on the real-world sustainability behaviours, and the achievements in-game are converted into an environmental effect [100-103]. Carbon footprint reduction games monitor real-life changes of lifestyle with points for environmental-friendly transportation, alterations in the diet, energy saving, or minimizing waste. Social aspects make it possible to have competitions, team efforts or community objectives which take advantage of social motivation. AI makes unique recommendations based on the personal situation, and proposes high-impact changes, taking into account the specifics of the location of the player, his/her resources, and limitations. Long-term monitoring represents cumulative effects and addition. Educational escape rooms have teams challenged with environmental puzzles where they have to collaborate, integrate and solve problems in an environment with time constraints. AI-based virtual escape rooms create scenarios, change the level of difficulty of the puzzles according to the performance of the teams, and give hints in case of stagnation of the groups. Themes may include avoidance of environmental disasters, find origin of environmental pollution, or finding resources to sustain the various problems. The collaborative and urgent aspect is to ensure engagement, whilst the puzzles instill environmental material and sustainability. Teams or individuals are competitive in leagues of sustainability, which play games that tackle challenges of environmental issues with AI ranking players, offering similar players matched with counterparts, and providing more difficult challenges to increased levels of players. Competitions that are seasonal allow lengthening the flow of engagement by introducing new challenges and contracting new chances to succeed. The features of spectators enable others to observe the best performers, and they learn using their tactics as they build social identity that encourages performance.

3.6 Applications of Natural language Processing.

NLP allows the AI to process and make sense of text around them, create, and generate natural language, and is applicable in a number of green education applications [7,9,104-106]. Automated essay scoring is used to judge the quality of writing by students on themes relating to the environment and it reviews writing by evaluating accuracy of the factual context, quality of argumentation, system thinking, ethical reasoning, and by writing mechanics. Expert-scored essay trained models offer reliable feedback scalably and identify aspects of improvement needed on the dimensions. Formative feedback does not provide the scores only, but identifies the strengths and weaknesses, explains the criteria of evaluation, and proposes the strategies of revising instead. Conversational AI tutors talk with students on topics concerning the environment and respond to questions, redress wrong beliefs, guide student inquiry, and invoke thinking. These systems use large language models which are fine-tuned on environmental content and pedagogical engagements to produce contextually relevant responses that will flex to student familiarity levels and learning requirements. Multi-turn conversations help to stay on track, offer a reference to the standards of the former conversation, and advance toward the learning goals in a gradual manner. The conversational interface reduces the obstacles among the students who feel shy to ask questions during the classes as well as offers unlimited patience and availability.

Table 1: AI Techniques and Applications in Green Education

Sr. No.	AI Technique	Application Area	Educational Purpose	Tools/Platforms	Key Features	Implementation Challenge	Future Opportunity
1	Machine Learning Classification	Species Identification	Biodiversity Literacy	iNaturalist, Seek, PlantNet	Real-time photo recognition, Citizen science integration	Limited accuracy for rare species	Integration with genomic data for enhanced accuracy
2	Natural Language Processing	Automated Essay Scoring	Climate Change Writing	ETS Criterion, Turnitin Revision	Instant feedback, Writing improvement suggestions	Limited assessment of creativity and critical thinking	Multimodal essay analysis including diagrams and data
3	Deep Neural Networks	Climate Modeling Simulations	Climate Science Education	En-ROADS, C-ROADS	Interactive parameter manipulation, Real-time visualization	Computational complexity for detailed models	Integration with local climate data for personalization
4	Computer Vision	Waste Sorting Classification	Circular Economy Education	RecycleCoach, Bin-e	Object recognition, Material identification	Variability in packaging and contamination	AI-guided disassembly for complex products
5	Reinforcement Learning	Adaptive Content Sequencing	Personalized Learning Paths	Smart Sparrow, Knewton	Dynamic difficulty adjustment, Mastery-based progression	Requires extensive interaction data for optimization	Lifelong learning profile maintenance across contexts
6	Generative AI	Educational Content Creation	Curriculum Development	ChatGPT for Education, Anthropic Claude	Rapid content generation, Multiple difficulty levels	Quality control and factual accuracy verification	Culturally adapted content generation
7	Recommender Systems	Learning Resource Suggestions	Self-Directed Learning	Khan Academy, Coursera	Interest-based recommendations, Skill gap identification	Filter bubble risks limiting exposure	Cross-platform recommendation integration
8	Time Series Analysis	Environmental Trend Detection	Data Literacy Development	Google Earth Engine, Planet Explorer	Historical data visualization, Pattern recognition	Data complexity and interpretation skills required	Predictive modeling for future scenario exploration
9	Sentiment Analysis	Climate Communication Analysis	Media Literacy	Brandwatch, MonkeyLearn	Emotion detection, Misinformation identification	Context-dependent sentiment interpretation	Real-time social media climate discourse tracking

10	Clustering Algorithms	Student Learning Profile Grouping	Differentiated Instruction	Learning Analytics Platforms	Behavioral pattern identification, Personalization grouping	Privacy concerns with student profiling	Dynamic cluster adaptation as students evolve
11	Neural Machine Translation	Multilingual Content Delivery	Global Accessibility	DeepL, Google Translate Education	Multiple language support, Cultural adaptation	Loss of nuance and context-specific meanings	Low-resource language support expansion
12	Semantic Segmentation	Land Use Classification	Geographic Information Systems Education	ArcGIS, QGIS with AI plugins	Pixel-level classification, Change detection	High-resolution imagery requirements	Integration with ground-based observations
13	Speech Recognition	Voice-Based Learning Interaction	Accessibility Enhancement	Dragon NaturallySpeaking, Google Speech-to-Text	Hands-free interaction, Transcription services	Accent and dialect recognition limitations	Emotion recognition from voice patterns
14	Predictive Modeling	Learning Outcome Forecasting	Early Intervention Systems	Civitas Learning, Brightspace Analytics	At-risk student identification, Success prediction	Algorithmic bias in predictions	Incorporating non-academic success factors
15	Graph Neural Networks	Ecosystem Relationship Modeling	Systems Thinking Development	Custom ecological simulation platforms	Network visualization, Relationship mapping	Complexity of representing indirect effects	Multi-scale ecological network integration
16	Bayesian Networks	Knowledge State Inference	Intelligent Tutoring	Cognitive Tutor, Carnegie Learning	Probabilistic reasoning, Misconception detection	Expert knowledge required for network structure	Automated structure learning from data
17	Optical Character Recognition	Environmental Document Digitization	Historical Data Access	Adobe Acrobat, Tesseract	Text extraction, Searchable documents	Historical document degradation challenges	Handwriting recognition for field notes
18	Anomaly Detection	Environmental Monitoring Alerts	Citizen Science Quality Control	Custom sensor network platforms	Outlier identification, Data validation	False positive management	Integration with expert verification systems
19	Multi-Task Learning	Integrated Competency Assessment	Holistic Skill Evaluation	Specialized assessment platforms	Multiple skill simultaneous assessment	Balancing different skill importance	Adaptive task selection based on student needs
20	Federated Learning	Privacy-Preserving Analytics	Ethical Data Practices	TensorFlow Federated, PySyft	Decentralized model training, Privacy protection	Coordination complexity across institutions	Global learning analytics while protecting privacy
21	Active Learning	Efficient Data Labeling	Training Data Development	Prodigy, Label Studio	Minimal labeling effort, Strategic sample selection	Requires initial labeled dataset	Continuous improvement with student contributions
22	Transfer Learning	Cross-Domain Knowledge Application	Efficient Model Development	Pre-trained models from TensorFlow Hub, PyTorch Hub	Reduced training data requirements, Faster deployment	Domain gap between source and target	Zero-shot learning for completely new contexts
23	Explainable AI	Model Transparency	Trust and Understanding	LIME, SHAP	Decision explanation, Feature importance	Explanation complexity for non-experts	Interactive explanation tailored to user expertise
24	Robotics	Environmental Sampling	Hands-On STEM Education	Arduino-based robots, LEGO Mindstorms	Physical interaction, Sensor integration	Cost and maintenance requirements	Swarm robotics for collaborative monitoring
25	Virtual Reality	Immersive Ecosystem Experience	Experiential Learning	Oculus Quest Education, Google Expeditions	360-degree environments, Presence sensation	Motion sickness and accessibility issues	Haptic feedback for enhanced realism

26	Augmented Reality	Contextual Information Overlay	Field Trip Enhancement	Pokemon Go-style apps, Google Lens	Real-world integration, Location awareness	Outdoor screen visibility challenges	Wearable AR for hands-free field work
27	Edge Computing	Offline AI Functionality	Low-Connectivity Environments	TensorFlow Lite, ONNX Runtime Mobile	Local processing, Reduced latency	Limited computational power on devices	Hybrid cloud-edge architectures
28	Blockchain	Verified Sustainability Credentials	Digital Badging Systems	Blockcerts, Learning Machine	Tamper-proof records, Portable credentials	Energy consumption of blockchain networks	Green blockchain alternatives
29	Optimization Algorithms	Sustainable System Design	Engineering Education	MATLAB Optimization Toolbox, Python SciPy	Constraint satisfaction, Efficiency maximization	Mathematical complexity for students	Interactive optimization with visualizations
30	Causal Inference	Impact Evaluation	Evidence-Based Practice	DoWhy, CausalML	Intervention effect estimation, Confounding control	Requires careful research design	Automated causal discovery from observational data

Empowering customized practice and formative evaluation, automated question generation generates experience problems, discussion questions, or assessment questions on the basis of environmental texts, thus generating these items on a large scale [6,107-109]. The systems based on AI are used to scan source documents and extract the most important concepts, and it further creates questions that aim at various levels of cognitive processes, whether recall or creating. The estimation of the difficulty of questions is used in adaptive testing as a means of efficiently testing the knowledge of the student. Multiple-choice questions have distractors that are generated according to widespread errors of English usage and make sure that items do not discriminate related to knowledge and guessing. Text summarization involves the fact that long environmental reports, scientific articles or policy documents can be summarized and thus made short, but without losing any important information, and is readable by students. Extractive summarization picks and includes significant sentences of source texts whereas abstractive summarization produces new summaries which can use other words and sentence structures compared to the original ones. Multi-granularity summarization gives short summaries in case of brief orientation, and detailed summaries in case of expansive research. AI does not only recognize the reading level and adapts the complexity of the summary to that level but goes further to ensure that expert knowledge is available to the learners who may be at various levels of development. Sentiment analysis is a study of using emotional overtones in environmental communication, which assists students in identifying persuasive features and detecting bias sources and the emotional aspects of environmental communication. Social media debates about environmental issues are also analyzed with the help of detecting the attitude and concern expressed by people, polarization, and misinformation disseminated by them. Students can find out how sentiment differs based on demographic categories, evolves overtime, or is based on partisan sources and acquire critical media literacy and awareness on the issue of environmental communication.Named entity recognition recognizes allusions to species, places, chemicals, organizations, and other environmental objects in text and allows them to be indexed, extracted to generate knowledge and interrelates similar information across documents. Entity relationship is recognized to display networks of actors in environmental governance, the interactions among species within ecological writings or the causal pathways within climate impact texts. It is these organized representations that render text based implicit knowledge explicit and thus analyzable.

In an analysis called misinformation detection, claims of the environment are evaluated against scientific consensus, logical fallacies are detected, misleading statistics identified, and sources that are likely to produce disinformation flagged. Students post claims that they was in the media and get their evaluations with explanations and giving them links to authoritative sources. This is the process that builds the skills of verification and disbelief in untested claims and proves the use of AI in quality of information. The content recommendation is a process of analyzing the interests, knowledge and the goals of students and recommending them the articles, videos, podcasts or websites concerning the environment presupposing unlimited information spaces. The recommender systems give relevance and variety so that the student gets exposed to perspectives and topics that he/she would not have pursued automatically. The explanation justifies the suggestions according to the profiles of the student or similarity with the content that has already been liked, and the reasoning is in favor of metacognitive awareness in seeking information. Estimates of the content difficulty guarantees that the recommendations do not incur frustrations or boredom due to recommendations being set at the wrong levels. Demining the environmental arguments Argument mining finds claims, evidence, and skeletons in environmental arguments, allowing their dissection of persuasive initiatives, examination of evidence quality, and identification of logical gaps. Students learn to build sound environmental arguments based on the feedback on the argument structure, the adequate support of the evidence and the ability to consider the opposing arguments. Argument comparison on environmental controversial issues have shown that everyone has reasoning patterns in their positions that allow one to critically analyse rather than just agree or disagree. Translation tools expose environmental education material to cross-language environments, which is a strategy to overcome the obstacles to sustainability knowledge in multilingualism. Neural machine translation can be used to provide almost human translations in a wide range of language pairs, making it possible to localize content quickly. Cultural adaptation does not just deal with literal translation but adapts examples, units of measurement, policy references and cultural framing to suit target audiences. Low-resource language support can be used to institute the environmental education to the indigenous and minority language speakers in a manner that respects linguistic diversity and disseminates sustainability literacy.

3.7 Computer Vision and Remote Sensing

Computer vision allows AI-assisted visual learning and environmental surveillance in green education as well as species detection and image learning through the analysis of images and video [110-112]. Automated species identification enables students to take pictures of organisms using smartphones and get an instant identity of the models that are trained using millions of labeled images. The tools help in democratizing taxonomic knowledge and make nature enjoyments a form of learning as a person adds observations to the biodiversity databases. Confidence rating and various species recommendations instill probabilistic thinking and require testing as opposed to blindly following technology findings. Satellite imagery property of land use and land cover add to the landscape and depicts the change in the environment, urban growth, deforestation, agricultural intensification, or ecosystem recovery at the regional, sub-regional, to global scales. Students examine satellite imagery time series, measure changes and study drivers with the help of socioeconomic data. Machine learning classifiers are often used to produce a high level of accuracy in identifying the type of forest, crop types, built environments, and water bodies as well, which makes the task of conducting more complex analyses that do not need manual interpretation. Such uses build up spatial reasoning, abilities to quantify, as well as to comprehend remote sensing technologies that are all gaining importance in the science and management of the environment. Environmental applications Object detection Object detection in environmental artworks can be used to identify animals in camera trap images, count the individual trees in aerial shots, or find plastic contaminations in ocean shots or illegal deforestation in near-real-time satellite feeds. Students are involved in training data labeling, and learning how human knowledge steers machine learning. The comparison of model predictions and ground truth demonstrates strengths, weaknesses, and failure modes of computer vision to form a critical opinion about the AI abilities instead of uninformed trust in technological solutions.

Change detection algorithms reveal the different changes in the environment by comparison of images of the identical location over a period of time thereby detecting changes in the environment. Automated change detection is applied on students to investigate glacier retreat, coral bleaching, urban sprawl, wetland loss or forest regeneration, which is then ground truthed and causation analyzed. Through these applications local environmental variations are linked to global trends as well as showing the potential of technology to provide monitoring of dimensions where it would be impossible to monitor directly. Semantic segmentation is a labelling method of every pixel in a picture based on its classification as environmental data and allows a detailed study of composition of landscape, structure of vegetation, or distribution of green space in urban regions. The learners discuss how semantic segmentation can be used in urban planning, measuring habitat connectivity, or precision agriculture. The pixel-based classification is a quantitative tool that measures areas, quantifies fragmentation, or monitors phenological changes on a pixel scale, which helps in scientific research and decision-making in the environment. Action recognition and pose estimation examine human behavior in videos, which makes it possible to evaluate outside education skills, methods of work in the field, or environmental sustainability. Models recognize body positions, monitor motions, categorize behavior like proper tree planting skills, proper water sampling steps, or sorting of a recycle material correctly. Changes in automated assessment deliver a scale-based feedback and relieve instructors of the burden of assessing at the lower stages of learning. Privacy-conserving strategies examine movements without any identifiable images being stored and trade the advantage of learning against the ethical consideration. Virtual experiences provided by computer vision recognize physical objects and environments and overlay virtual material onto them, to provide blended learning environments. Students use the point mobile devices on plants to view virtual flowers, fruits or pollination animations to explain the process of reproduction. The image recognition or the QR code can also be used to activate the educational material once the students perceive the environmental features during field trips. Spatial mapping allows one to place permanent virtual objects in real spaces, and with this technology, one can carry out the AR activities collaboratively under the participation of several students sharing the virtual images.

Visual question answering systems are systems that recognize pictures, respond to natural language queries on what is depicted in an environment. Students send field observations in the form of photographs and questions on the behaviors, species, conditions or processes, and are given explanations which relate the images with ecological concepts. Such multimodal interface facilitates inquiry learning and also allows different forms of questions that are not expected in the application development. Crowdsourced imagery used to monitor the environment gathers photos taken by students and other members of the community, uses computer vision to identify patterns, anomaly or changes. Students take photos of stream conditions, invasive species events or weather conditions with automated analysis identifying trends, creating alerts or setting focus on follow up investigation. Participatory monitoring builds a level of community ownership of their environment and also creates useful information in the form of research and management.

3.8 Analytics of Learning and Educational Data Mining.

Learning analytics and educational data mining build on AI to derive insights into educational data and guide win instruction, customize learners expectancy, and grow knowledge about the way learners become environmentally literate. Predictive models are used to predict student outcomes such as course completion, knowledge acquisition or behavior change intentions on the basis of the early interaction processes in order to implement proactive interventions to help struggling learners [96,113-115]. The importance of features analysis can be utilized to find aspects that are the most influential predictors of outcomes and thus where improvement is to be made. With the help of clustering algorithms, it is possible to distinguish among various archetypes of learners according to behavior, knowledge profiles or learning preferences, which allows distinguishing between various learners to assist them with differentiated instruction and allocating resources targeted to that specific learner. The small groups may be individuals who like to explore on their own and are equally independent learners, students who learn in an organized manner and prefer an order of instructions, and those who struggle with learning. Membership of a cluster facilitates the provision of pedagogical adaptations and communication plans without any use of stereotyping by acknowledging the fact that people have characteristics of both types with time changing them. There is the sequence mining which figures out typical learning patterns using learning materials, highlighting which strategies work and which do not, which concepts are essential to the learning process or where learners tend to falter. The identification of optimal paths implies favorable learning paths and at the same time, indicate areas where the curriculum design is posing an undue confusion by poor sequencing of the subjects. Deviation analysis identifies the abnormals in terms of interaction that can point to confusion, lack of engagement, or new approaches to solving the problem and should be investigated.

Social network analysis studies the patterns of collaboration, sharing of knowledge and peer influence within learning communities in the environmental learning context. Network visualizations identify the central people who are knowledge brokers, lone students who need socialization, and cluster visualizations indicating the creation of subgroups. The models of influence propagation follow the spread of environmental attitudes or sustainable behaviors over the social networks and show the processes of changing the social environment. Network interventions are organisations being strategic to network individuals with an aim of enhancing the quality of collaboration or speeding up knowledge dispersion. Discourse analytics uses natural language processing to engaged discussions asynchronously, synchronously in chats, or collaboratively in documents, where the quality of participation, knowledge-making and collaborative process is evaluated. Automated coding takes place to detect question-asking, explanation-giving, critique, synthesis, and other useful discourse moves and give feedback to the students and instructors. Topic models uncover themes of debate and the presence or absence of discussions that can deal with the intended learning goals. Sentiment tracking identifies frustration, confusions or excitement, which allows affective assistance. Time series analysis looks at the time trends of engagement, increase or decrease in knowledge or behavior change, differentiating between long-term trends and short-term changes. Early warning notices teachers of loss of initial energy, and retention intervention can be put into place. Learning curves of various instructional methods are compared to find more useful pedagogical methods. The lag effects show the latent effects of educational interventions that should not be evaluated on short-term basis. Multimodal learning analytics combine a variety of data streams such as clickstream data of learning technology, eye tracking revealing the focus of attention, physiologic sensors to cognitive load and emotional arousal, as well as videos of facial expression and body language. Machine learning layers these modalities in order to identify engagement states, cognitive-affective-behavioral patterns of learning, and productive and unproductive occasions of struggle or confusion. Multimodal approaches offer deeper insights compared to any amount of individual data and need to be sensitive to privacy issues.

The automated feedback generation uses learning analytics to generate individual message depending on the performance, outlines performance, determines weak and strong areas of action, and suggests the necessary actions. Natural language generation provides sufficient feedback in the form of encouraging tones, and promptly offers unbiased appraisals to the learner, according to the preference of the learner. Feedback timing optimization would figure out at what time the intervention is most productive so that neither a situation can be jeopardized by being given a lifeline before fighting productively nor given a lifeline too late when the false beliefs have already solidified. Associated with reflection, data awareness, and decision making, dashboards provide learners and educators with the presentation of analytics. Learner facing dashboards indicate progress and compare performance to peers or previous self as well as suggest learning activities. Teacher dashboards are used to indicate that a student needs to be addressed, to provide an overview of the student do on the class level, and propose changes in instruction. Graphic design strikes the right balance between a substantial amount of information and meaningfulness so that the conclusions will be practical instead of overwhelming. Ethical schemata of analytical systems in learning deal with consent and privacy, fairness, transparency, and proper utilization of the learning data. Learner autonomy is not violated and the analytical power is however diminished through opt-in approaches. Different privacy and federated learning safeguard individual privacy and allow aggregate revelation. Algorithms will identify biases that harm certain organizations. Being transparent on what data is being gathered, the way it is analyzed and what the analytic data informs makes people trust and makes informed consent possible. Purpose limitation is by ensuring that analytics are limited to educational goals and mission creep into surveillance is avoided.

3.9 Environmental Surveillance and Citizen Science.

In practice, the AI-sustained environmental surveillance is a combination of sensor networks, satellite-based monitoring, and community observations that would offer real information regarding the inquiry-based green education as well as add to the body of scientific knowledge and environmental management [96,116-119]. Low cost sensor networks monitor air quality, water parameters, soil conditions or microclimate variables generating real-time streams of data that are available to students via web dashboards or mobile applications. Machine learning compares sensor data and finds events of pollution, identifies tendencies, alarms, or confirms that the measurements are good or bad. Air quality monitoring is used through the use of a network of particulate matter, ozone, nitrogen dioxide, or volatile organic compounds sensors that are placed by schools and students. Predictive models of AI reveal the hourly concentrations depending on the meteorological conditions, the traffic, and the emission sources and allow comparing the observations to predetermined predictions in order to comprehend the nature of air pollution. The source apportionment algorithms are used to estimate whether there are contributions of traffic, industry, biomass burning processes, or natural source and this indicates the impacts of various activities on air quality. Health impact calculations are converting the concentrations into the risks where environmental factors are related to human wellbeing.

Water quality monitoring incorporates the work of students on the collection of samples and the implementation of chemical, biological, and physical tests to obtain the results, while the AI systems compile them, define spatial and temporal trends and define events of possible contamination. Benthic macroinvertebrate recognition on photographs uses computer vision, which allows hostile evaluation of stream wellbeing without utilizing the expertise, or taxonomy. Watershed modeling is a simulation mode of interaction between land use modifications and water quality and can enable students to know the association between activities in upstream and water condition downstream. Large datasets are created by camera trap, acoustic sensor, or eDNA sampling methods of biodegradation surveillance, which need to be automated to analyze the information. Computer vision identifies animals in images in camera traps and acoustic identifies them by species-specific sounds to determine present and approximate numbers. Based on AI-analysed observations, students deploy sensors, retrieve data and research ecologically important questions. Occupancy modeling takes into consideration imperfect detection explaining statistical thinking of observation activities. Engagement in long term monitoring shows the trends and conservation results of a population. Phenology observations using seasonal observations of leaf out, flowering, fruit set, migration or reproduction indicate changes in climate effects on ecological synchrony. Students take photos of plants at periodic points in which phenological stages are detected by AI. Writings of the data by geographical gradients of observations depict spatial change in timing and variation with years. Climate change is seen through detection of alarming decoupling between interacting species including plants as well as pollinators.

The invasive species tracking utilizes AI-based species recognition in relation to prompt recognition and early intervention. Students take snapshots of the suspected intruders with immediate recognition and instructions of reporting procedures. The spatial modeling forecasts the threat of invasion according to the distribution of species as well as the environment and human activities in order to determine the areas that monitoring needs to be concentrated on. Removal effectiveness monitoring enables the establishment of how the management activities impact on the populations in the long-term. Plastic pollution surveillance involves the students in gathering, classification, and estimating waste and inputting the records to the world databases. Recognition of images adapted to speeding up the categorization of the items collected in terms of type and brand. The accumulation zones and possible sources are shown through spatial analysis. The temporal trends determine whether the interventions related to pollution reduction reduce the pollution loads. Lifecycle analysis links the observed wastes with the consumption trends and disposal facilities. Urban heat islands are monitored by using temperature sensors and thermal cameras to map a temperature difference across urban locations and explore the impact of vegetation, pavement, material of the building, and urban form. Machine learning forecasts temperatures on the basis of satellite-based land cover and built environment attributes that allow students to plan the cooler neighborhood by means of a green infrastructure and changes in urban planning. The exposure assessment of heat compiles the temperature-related information with the demographics, which discloses the aspects of environmental justice. The quality of the noise in soundscape is recorded in documents related to noise pollution in terms of noise level measurements and sounds audio recording. In AI, sound sources are grouped on the basis of traffic, aircraft, industrial sound or biological sound as the distinguishing features. Psychoacoustic measurements determine the effect of annoyance and the effects of sound on health beyond the contribution of decibel levels. The identification of quiet areas leads to the urban planning that preserves acoustic environments that promote wellbeing and wildlife. Monitoring the state of soil health entails the physical, chemical, and biological indicators whereby the students would make field measurements and laboratory examinations. Aggregated data displays the Distribution of land use, management practices or contamination. Predictive models are used to estimate the potential of carbon sequestration, crop growth or erosion potential of the soil, depending on its properties. Regenerative agriculture proves to be useful with the tracking of improvements.

3.10 Sustainability Evaluations and Carbon footprints calculators.

Sustainability assessment tools that are driven by AI will allow students to analyze the impact of products or activities, organizations, or systems on the environment, building life science and quantitative environmental literacy. The carbon footprint calculators are used to estimate the individual lifestyle, organizational and product lifecycle carbon footprint of Greenhouse gas emissions generated and complex data interpreted into measurements that are easy to access. In instances of data gaps, machine learning models can be used to fill the data gaps and predict emission factors of certain activities and can also customize the calculations on rich or limited information of the user depending on the availability of data. With the help of personal carbon footprint applications, students are oriented to evaluate transportation, housing energy consumption, diet, consumption, and waste production. AI poses dynamic questions and makes them simpler to use by the younger audience, or more precise by the faster learner with advanced interests. Visualization is made in relation to a personal footprint in comparison to national averages, sustainable targets, or planetary borders. Categorical breakdown finds areas of the greatest impact that should be given attention. The scenario modeling shows the emission cut offs due to certain behavioral change and it Bodes a step, push by making plans realistic. The plane of scope classifies direct emission, purchased electricity, and value chain emission, the boundaries of the systems, and accounting conventions. Uncertainty quantification recognizes the limitation of data and error of estimate and creates advanced knowledge bigger than false accuracy. Benchmark comparison provides performance assessment based on how other similar organizations or the industry perform.

The applications of product lifecycle assessment identify the manufacturing, disposal, use and manufacturing of their products as well as raw materials originating their environmental impact. Students create products, approximate or study the lifecycle stages and compare environmental profiles. Hotspots identification shows what life cycle stages have the largest proportion of total impacts, to help in improvements of eco-designs. There are trade-offs between various environmental issues as climate is assessed, water use, and toxicity, resource depletion, and ecosystem destruction are all covered as multi-impact assessment. Tools that are simplified trade accessibility to education with methodological rigor, introducing concepts without being challenging to understand. Food sustainability measurement gauges the environmental effects of the food intake including greenhouse effect, land use, and water consumption, and biodiversity effects. Students produce meals or entire diets which sustainability scores and comparisons are provided. Cultural sensitivity observes the different food cultures but will also give information so that people can make informed decisions. Nutritional integration brings about the fact that environmental concerns do not undermine health and there is a need to understand that healthy local diets can be tasty. The mode comparison of transportation determines the emissions, air pollution, cost, time, and the health effects of various channels of traveling between particular sources and destinations. Students explore the process of commuting or taking long-distance journeys, or moving freight, and learn that the best decisions are based on situations. Infrastructure affects the revelation of how the built environment is shaped in transport choices is a representation of systems thinking of mobility transitions. The behavioral nudge implies constructive options at the lowest cost and inconvenience.

The model of energy systems allows the students to build the renewable energy systems of buildings, communities or regions. AI takes a rational decision of the solar panel orientation, wind turbine location, battery storage size and grid connection in order to involve intermittency, demand trends, and expenditures. The parameters are manipulated by the students to see the impacts on reliability, economics, and emissions. Comparison to fossil fuel systems quantifies benefits of the transition besides uncovering challenges that need to be addressed. Circular economy assessment can be used to determine the products and systems in terms of circular principles, such as durability, repairability, recyclability, and recycled content. The rating of the products through circular metrics is used by the students in the comparison between linear and circular business models. The material flow analysis also tracks the use of resources in the form of streams in the economic systems and detects areas of waste and closure. The principles of the circular design direct the learners developing product concepts that reduce environmental effects by being circular. Sustainable development indicators dashboards are collections of environmental, social, or economic measures of community, region, or country. The relations between indicators that show environmental improvements and cost versus benefits of the economies or benefits to the society are explored by students. Time series display improvement of sustainability objectives or alarming decline. Peers comparison determines the high performing jurisdictions that they can learn. Data storytelling tools enable students to make the findings presentable to the different audiences in a convincing manner.

3.11 One-to-One and Custom Learning

Personalization is one of the key AI promises that make education green, where learning is customized to individual factors, needs, goals and to deliver educational quality and equity. Student modeling integrates direct profile data such as demographics, previous knowledge, learning goals and preferences with derived aspects based on patterns of interaction, performance records and test scores. Extensive student paradigms facilitate advanced adjustments in a number of dimensions at the same time. Content personalization is based on changing the learning material according to the level of student knowledge, their hobbies and preferences. Prerequisite knowledge changes the level of explanation giving basic knowledge to beginners and not wasting time offering the same to the experts. Interest alignment chooses examples, applications and contexts which address student passions, whether in the form of wildlife conservation, technology in renewable energy, sustainable fashion or environmental justice. Modality variation introduces information in the form of text, video, interactive simulation, or even in the form of hands-on activities depending on the choice of style of learning, however, research questions the effectiveness of style-matching. Difficulty adaptation keeps the challenge levels to an optimal level that is not too easy or at a level that is too challenging. The dynamic difficulty adjustment is a performance tracking that becomes more challenging when succeeding and eases the challenges when you fail. Scaffoldings give suggestions, materials or worked examples to students in case of difficulty that gradually fade away as competence is achieved. Progression based on mastery does not allow one to advance till the prerequisite concepts are learned, and flexibility in pacing allows different speeds of learning. Pathway personalization establishes unique sequences using the learning material and instead of every student learning the same sequences. Prerequisite-based sequencing makes sure that conceptual backgrounds come before the dependent ones and gives different sequences where the prerequisites permit it. Goal oriented pathways emphasize content that has relevance to the student goals; be it preparing to the exam, personal growth or his future career. Interest exploration can be used to enable students to follow their interest but in the course of guaranteeing that all the key concepts are covered courtesy of guided discovery. Temporal personalization conforms to the availability, attention and most effective learning of students. Microlearning divides content into short modules to fit into the busy life or short attention span. Space algorithm is used to spread out practice across time to maximize retention, as opposed to cramming. The time-of-day adaptation is a very challenging cognitive task in the mind of the student where the performance patterns would often likely dictate that a student is at his best. Liberation of deadlines allows the various duties without losing accountability.

Affective personalization is a reaction to such emotional conditions as frustration, boredom, anxiety, or flow. Interaction-based frustration detection, performance trajectory, or self-report-based frustration detection elicits supportive interventions of encouragement, hint, or modification of tasks. Disengagement behaviors trigger boredom that in turn triggers more engaging activities or applications. The minimization of anxiety may take the form of low-stakes practice, growth mindset messages, or relaxation instructions. Sweet difficulty balancing fluid state of flow contributes to maximum engagement and learning. The process of social personalization changes the collaborative characteristics to individual social preferences and needs. Extraverts get more chances of interacting with peers whereas introverts get individual options. Competitive learners will also work with leader boards and challenges whereas collaborative learners will work on team projects. Mentoring pairs struggling students with successful students who would provide mentorship. Community features are the features of students sharing interests or balancing knowledge. Cultural personalization acknowledges and values various worldviews, knowledge systems, values, and exposes the students to more perspectives. New situations and examples demonstrate different cultures and experiences so that it is relevant and respectful content. Integration of indigenous knowledge appreciates the traditional perspectives and scientific views on ecological knowledge. Presentation of content value-giving to content takes into consideration that sustainability holds diverse meanings within diverse cultures and cultural imperialism should be avoided. The linguistic personalization has content in native languages or the complexity is changed depending on the language proficiency levels.

The personalization of metacognitive is helpful in the development of self-regulated learning as it depends on the metacognitive ability levels among oneself. Clear strategy teaching offers learning styles to students who do not have effective strategies. Metacognitive prompting promotes planning, acting as a monitor, and give assessment of the learning processes. Adaptive prompting frequency harmonies are facilitative and developmental of autonomy. The feedback of learning analytics lets students know what their trends and their progress are. Personalization of accessibility makes sure that the students with disabilities can receive green education with features that support them in relation to their needs. The visual impairment is supported by use of screen reader compatibility, alternative text and audio descriptions. The transcripts and captions support hearing impairment. Learning disabilities are facilitated by simplified language versions and the support to visuality. Motor accessibility allows the interaction with fine motor control. Accommodation of neurodiversity help minimize sensory overload or offer organization to executive functions impairment.

3.12 Challenges and Limitations

Although the use of AI in green education has achieved promising results, there are major challenges that it has to resolve through consistent focus and innovation. Digital divide results in the gross inequities in access to AI-mediated learning technologies that the schools and rural areas, as well as developing countries, do not have the required infrastructure in the form of reliable internet access, sufficient computing devices, and technical support. These inequalities face the risk of further inequality in education, with AI advantages being concentrated in already-privileged groups and this leaving vulnerable people most susceptible to environmental destruction. The issue of digital equity can be reduced by not only provision of technology but also training of teachers, provision of culturally relevant content as well as proactive funding schemes. Algorithms becomes biased as a result of training data, feature engineering or model design that makes a priori assumptions and/or is stereotypical and restricted or biased. Poor representation of some groups in training data results in models which do poorly on the populations. Such historical prejudices in education data are sustained in prediction, which could constitute a self-fulfillment prophecy, which restricts opportunities. Recommender systems can increase filter bubbles, restricting the views on various environmental views. Species identification systems that have been trained on temperate species do not work in places with more biodiversity such as the tropical. To reduce bias, it is necessary to have a variety of teams developing such a program, selective data curation, AI auditing, and community feedback arrangements The privacy of the information is compromised due to massive gathering and processing of student data such as learning behaviors, knowledge levels, emotional reactions as well as personal traits. Malicious actors might abuse sensitive information, use it in business, or publish it in an unacceptable manner. Because of power asymmetries and data practices complexity, students and families can have no meaningful consent. Compliance with regulation is also different in a variety of jurisdictions posing legal obstacles to global platforms. Different privacy-preserving strategies, such as the use of differential privacy, federated learning, and on-device processing, can protect against risks and, in general, lower analytic capability or the personalization effect.

The ecological footprint of the AI systems works against the principles of sustainability when model training and inference processes, which demand large amounts of energy, lead to massive greenhouse gases, especially when fossil fuel electrical energy is used. Massive computational resource is needed to train large language models with large carbon footprints. Major data centers with AI systems use vast amounts of water to cool them down. E-waste disposal due to the short-lived devices to benefit of the

AI education is a source of pollution and resource depletion. Environmental costs should be quantified with educational benefits alongside Lifecycle assessment of AI educational technologies they are to support the creation of more sustainable methods. Pedagogical issues challenge the APIs on the premise that it is not truly improving learning but simply automated without resulting in any changes in educational quality. Too much use of technology can reduce human existence, affectionate bonds as well as social training, which are vital to environmental education. Techno-solutionism runs the risk of providing educational challenges with a solution, which does not consider the root causes, such as, lack of teacher training, funding, or curriculum that is not aligned with the needs of the community. The reason replacement of an outdoor experience based learning with screen activities is against the principles of green learning is because it is more of an interest that is based on direct contact with nature and thus helps to develop emotional attachment to the environment. The resistance or poor preparation of the teacher is a barrier to successful implementation of AI in cases where the teachers are not aware of the capabilities and limitations of AI, do not have training about effective implementation, or are unsure of their technological adequacy. The improvement of professional development is usually focused on the technical functioning of these technologies instead of pedagogical intermingling or critical analysis of AI gadgets. Educators can feel the threat imposed on their experience or independence by AI instead of increased capabilities. By infecting teachers as co-designers but not end-users, there will be a sense of ownership and AI is not expected to harm professional practice but rather enhance it.

The issue of transparency and explainability might also be encountered when complex AI models are used as black boxes because the decision they make cannot be understood and criticized by educators and learners. Interpretability negatively influences trust, does not allow meaningful human oversight, and does not promote educational activities about AI systems themselves. The explainable AI approaches can give an idea about the thinking processes of the model, but the explanations can be too simplistic and can miss certain important factors. There are trade-offs between the interpretation of the performance of models and their execution, such that negotiation is context dependent. Scalability issues do not allow successful small-scale pilots to scale to millions of learners because of the computational costs, content development needs, problems with quality assurance, or maintenance needs. Individualization of personalization demands a lot of data processing in each learner and more processing as the number of users grows. The production of high-quality content requires the time and effort expertise that is hard to replicate. Technical infrastructure is not capable of sustaining huge simultaneous users at peak times. Sustainable scaling needs to be done with a close system architecture, an effective algorithm, automatic content generation, and business models that provide sustainability. The lack of cultural appropriateness arise when artificial intelligence systems that have been trained in specific cultural situations assume the application of specific assumptions, values, or knowledge that are unsuitable or offensive in a different culture. The value systems of the indigenous knowledge systems about the ecological wisdom may be put on the back burner by the Western scientific worldviews. Among the examples provided in the text and their applications, there can be references to the unknown context or confirmation of the cultural stereotypes. Support of minor languages restricts the access to the language minority speakers. The culture responsive development of AI is a process that has diverse stakeholders engagement, localization other than translated, and acknowledging the existence of various legitimate knowledge systems.

Assessment validity raises the concern of whether the AI systems can measure specific aims of learning as opposed to proxy variables or gaming the system. Specific metrics can encourage superficial learning and simple memorization instead of in-depth knowledge and the ability to learn to automatic tests. The standardized methods can fail to reflect the local or culturally specific knowledge of sustainability and environmental issues of concern. To take care of validity, assessment must be matched with learning outcomes, a variety of methods of evaluation and validation of human judgment. The ethical issues touch ethically informed consent, proper use, equitable sharing of benefits, prevention of harm as well as responsibility. Students would not get to know what information is being gathered and its impact on their learning. The application of AI in making decisions regarding education opportunities needs to be clear and should have an appeal channel. Populations that lack access to benefits should be targeted as opposed to its concentration among the privileged groups. Stereotypes, intrusion of privacy, or psychological effects that Hamas embarks on should be prevented and compensated. The structure of accountability should be in relation to AI failures or abuse, but the problems of responsibility of developers, deployers, and users are complicated.

3.13 Opportunities and Future Directions.

Nevertheless, AI-based green education is a great challenge that opens the great opportunities of innovation, impact, and advancement towards the sustainable development objectives. The advent of new AI functionality allows subsequent and more advanced applications of the existing limitations and new educational patterns use AI opportunities to develop in innovative ways that would otherwise have been impossible in the course of traditional education. Multimodal AI systems which are products of vision, language, speech, and sensor processing can be utilized to create rich learning experiences as a combination of visual observation, verbal interaction, textual information, and environmental data. Students were able to take pictures of organisms in the natural environment, to ask questions and to get answers through the oral presentation, view them with the corresponding images and video materials and to have access to the appropriate text materials. Multimodal cognition makes AI systems perceive more complicated scenarios, offer context-specific help, and facilitate multi-way interaction desirability. Physical education Physical embodiment of AI to robotic systems forms physical educational agents that can interact with environments and learners in ways that are not screen-based. Environmental education robots may even go with students on nature walks, pointing at interesting features, answering questions, taking samples, or physical interaction to show ecological concepts. It is possible that companion robots would promote sustainable practices, give emotional support in difficult learning, or it could be a collaborative effort. The application of social robotics in the field of environmental education is a relatively undeveloped concept but has interesting potentials.

Neuroadaptive systems observe brain activity, eye movement or a physiological reaction and manipulate the instruction on the basis of the cognitive state with superior precision than ever in history. In instances where sensors are used to detect cognitive load, the systems might simplify information, give breaks, or alternate modalities. The confusion recognition would invoke clarifying interventions and detecting deep concentration would reduce the interruptions. Neuroadaptive methods though still in the experimental stage may maximize the learning efficiency and also demonstrate the cognitive mechanisms that lead to environmental knowledge. Affective computing systems study and react to emotions based on facial expressions, voice tone, text affection or physiological indications, and agree with the emotional aspect of environmental education. Frustration in the situation involving complicated sustainability issues results in support or other interpretations. The worry on climate change is given sympathy consideration and agency-building contents. Favorable emotional reactions to nature experiences are supported and elongated. Considerable yet prudent use of affective AI can improve connectivity and health and increase privacy and manipulation issues that must be maneuvered. Collective intelligence systems pool together individual student knowledge, observations and resolutions to environmental issues to create greater fund of knowledge than the same cannot supply. Students across the globe would be able to work on climate change initiatives, biodiversity surveillance, or sustainability innovations, with AI making coordination and integration of efforts and pointing out new trends. Collective intelligence practices show cooperation on the scales within the context of global environmental issues and also create community and common purpose.

AI-oriented content generation tools facilitate the creation of an active curriculum in relation to new problems observed in the environment, local setting, and needs of a person. Generative models develop learning modules on recent occurrences in the environment, generate practice problems on certain issues, or use simulations to demonstrate certain ideas. The automated content generation method tremendously decreases the development time and cost that allow it to be updated frequently and customized on a large scale that was not feasible with manual creation. The mechanisms of quality assurance will guarantee the lack of inaccuracy, inappropriateness, and un-pedagogical quality of generated material. Sustainability solution designers, ecological art makers, as well as environmental communication campaign designers can use augmented creativity tools. AI makes design changes and judges ideas by sustainability standards, creates visualizations of ideas, or mixes ideas of learners with professional methods. These instruments scaffold the creative processes but leave the students in charge and ownership. Creativity augmentation shows AI at its best of human abilities when wisely applied. Lifelong learning ecosystems incorporate formal education with informal learning, professional growth and community engagement in lifelong, and AI helps in smooth transition and links. The sustainability efforts towards the same that begin during childhood can be maintained into the career sphere through career-specific sustainability training, volunteering in local conservation, and retirement leisure pursuits with AI tools to sustain learner profiles, offer relevant opportunities, and adjust to changing interests and capabilities over the lifelong. The ecosystem approaches acknowledge the fact that sustainable societies need to undergo never-ending learning, as opposed to the time-bound schooling.

Interdisciplinary integration de-silos to an extent that it involves the use of the topics of the environment to contextualise mathematics, language and arts, and social studies as mathematics, literacy and other skills allow understanding of the environment. AI establishes cognitive links between disciplines, proposes activities of integration, and evaluates interdisciplinary competencies. The real-life environmental issues that involve multiplicity of knowledge make education organization centers but not separate branches of science. The integration of indigenous knowledge is a respect to the indigenous traditional knowledge of ecology, land management and the worldview, with the inclusion of indigenous knowledge in conjunction with the scientific viewpoints. Machine translation of indigenous cultural knowledge AIs allow control over access to knowledge and cultural protocols that may preserve and transmit knowledge created by the indigenous community. Preservation efforts of endangered languages ensure that the languages are used as a medium of environmental knowledge. That needs native leadership, the sharing of benefits and the intellectual property rights.

Climate change education innovations equip students with golden opportunities of early adapting to the fast-changing environments, chronic stresses, and acute occurrences of disasters that are rapidly and steadily impacting communities in various parts of the world. Scenario planning simulations consider the various possible futures by alternative availability of emission pathways and adaptation approaches. Building of resilience creates a level of responding to disruptions without compromising wellbeing. Cognitive reactions to climate anxiety and grief result in psychologically healthful engagement as opposed to denial and despair. Action competencies enable students to be stalemates of mitigation and adaptation, and not merely passive victims. As a field, environmental justice education focuses on distributions of environmental benefits and burdens by social groups and the distribution of marginalized populations who experience disproportionately impacts of pollution, effects of climate change and loss of resources. Statistics on environmental injustices are brought to light through data analysis and resistance and advocacy can be viewed through case studies. Environments and demographic information are analyzed by artificial intelligence that determines inequalities and monitors justice interventions. This education develops the sense of equity aspects that are determining even just sustainability transitions. Policy literacy is the creation of students who know how to be able to understand and participate in environmental governance such as regulations, incentives, international deals, and political procedures. The policy negotiation simulations can be said to be complex in the challenge of ensuring consensus among the parties of interest that have conflicting interests. Policy impact analysis on the environmental outcomes and social groups advances the analysis skills critically. Students can be taught youth advocacy training that will enable them to engage in democratic procedures that involve their future in the environment.

With an explicit development of skills of perceiving complex dynamic, and interconnected systems that are at the heart of environmental issues, systems thinking pedagogy is intentionally constructed to develop such understanding. Causal loop diagramming will show feedback mechanisms of system behaviors. The accumulations and rates are quantified in stock and flow models. The use of leverage points specifies the areas of interventions with the most impact. Inquiry of unintended consequences builds modesty regarding the effectiveness of intervention. The concept called systems thinking is moved across contexts, i.e. between the ecosystems and economic systems to the social systems. Futures literacy develops the ability to envision and to construct desirable futures instead of becoming obsessive about the existing paths. Visioning exercises reflect positive desirable sustainable futures that action is directed. Back casting derives the futures between goals to the present. Scenario planning deals with the possible futures that may happen as a preparedness against uncertainty. The futures thinking becomes a solution to the short-term prejudices hindering a long term strategizing.

Table 2: Challenges, Opportunities, and Future Directions in AI-Driven Green Education

Sr. No.	Challenge Category	Issue	Current Impact	Mitigation Approach	Emerging Opportunity	Research Gap	Future Direction
1	Digital Equity	Infrastructure Disparities	Exclusion of resource-poor communities	Offline-capable applications, Low-bandwidth optimization	Mobile-first platforms, Community technology centers	Effectiveness of equity interventions	Universal basic digital infrastructure initiatives
2	Algorithmic Bias	Training Data Imbalances	Poor performance for underrepresented groups	Diverse data collection, Bias auditing tools	Participatory AI development	Cross-cultural validation studies	Fairness-aware algorithm development
3	Data Privacy	Student Information Protection	Surveillance concerns, Consent challenges	Privacy-preserving techniques, Transparent policies	Federated learning, On-device processing	Long-term privacy impact assessment	Privacy-by-design educational platforms
4	Environmental Footprint	AI System Energy Consumption	Carbon emissions contradicting sustainability goals	Energy-efficient architectures, Renewable-powered data centers	Green AI development metrics	Lifecycle assessment of educational AI	Carbon-neutral AI infrastructure
5	Teacher Preparation	Inadequate AI Integration Training	Ineffective implementation, Resistance to adoption	Comprehensive professional development, Co-design approaches	Teacher-AI collaboration models	Longitudinal teacher learning trajectories	AI literacy as core teacher competency
6	Pedagogical Soundness	Technology Without Learning Science	Ineffective education despite technological sophistication	Evidence-based design, Learning science integration	Learning engineering approaches	Causal impact studies of AI interventions	Theory-driven AI educational design
7	Cultural Appropriateness	Western-Centric Knowledge Systems	Marginalization of indigenous and local knowledge	Participatory design, Cultural consultation	Pluralistic knowledge representation	Comparative cultural effectiveness studies	AI supporting multiple knowledge systems
8	Assessment Validity	Measuring Proxy Variables	Gaming systems, Narrow skill focus	Multiple assessment methods, Authentic tasks	Performance assessment automation	Construct validity of AI assessments	Holistic competency measurement
9	Transparency Deficits	Black Box AI Systems	Lack of trust, Limited oversight	Explainable AI techniques, Interpretable models	Model interpretability as educational content	User understanding of explanations	Adaptive explanation systems
10	Scalability Limitations	Computational and Content Constraints	Limited reach of successful pilots	Efficient algorithms, Automated content generation	Edge computing, Generative content AI	Sustainable scaling models	Global platform architectures
11	Outdoor Learning Displacement	Screen Time vs Nature Contact	Reduced direct environmental experience	Blended approaches, AR for outdoor enhancement	Nature-based technology integration	Optimal technology-nature balance	AI-augmented field experiences
12	Misinformation Vulnerability	AI-Generated False Content	Spread of climate denial and greenwashing	Fact-checking integration, Source verification	Critical AI literacy education	Detection of AI-generated misinformation	Provenance tracking for educational content
13	Evaluation Rigor	Insufficient Impact Studies	Uncertain effectiveness, Evidence gaps	Randomized controlled trials, Longitudinal studies	Rapid experimentation platforms	Long-term behavioral change measurement	Continuous evaluation ecosystems

14	Intellectual Property	Content Ownership Ambiguity	Unclear rights for AI-generated materials	Clear licensing frameworks, Open educational resources	Commons-based content development	Legal precedents for educational AI	Balanced IP frameworks
15	Ethical Governance	Lack of Oversight Mechanisms	Potential for misuse or harm	Ethics review boards, Community participation	Participatory governance structures	Stakeholder perspectives on AI ethics	Adaptive ethical frameworks
16	Accessibility Barriers	Disability Exclusion	Inaccessible interfaces and content	Universal design, Assistive technology integration	AI-powered accessibility features	Effectiveness for diverse disabilities	Proactive accessibility AI
17	Language Limitations	Dominance of Major Languages	Exclusion of minority language speakers	Multilingual NLP, Translation services	Low-resource language AI development	Minority language educational effectiveness	Language preservation through AI
18	Socioeconomic Segregation	Differential Access Quality	Widening achievement gaps	Subsidized access, Equitable distribution policies	Community-owned platforms	Impact on educational inequality	Universal green education access
19	Behavioral Change Transfer	Learning Without Action	Knowledge-action gap persistence	Action-oriented pedagogy, Real-world integration	Behavioral nudging AI, Habit formation support	Mechanisms of educational behavior change	Sustained impact measurement
20	Interdisciplinary Integration	Siloed Development	Limited holistic approaches	Cross-sector collaboration, Systems perspectives	Convergence research initiatives	Effective collaboration models	Integrated research-practice partnerships
21	Commercialization Pressures	Profit Motives vs Educational Goals	Feature proliferation, Marketing over efficacy	Public investment, Non-profit models	Social enterprise approaches	Business model sustainability analysis	Mission-driven educational AI
22	Rapid Obsolescence	Fast Technology Evolution	Constant upgrading requirements	Sustainable update cycles, Core capability focus	Modular, interoperable systems	Technology lifecycle in education	Future-proof architecture design
23	Attention Economy Concerns	Addictive Design Patterns	Unhealthy technology relationships	Well-being centered design, Time limits	Mindful technology use education	Impact of design choices on wellbeing	Ethical attention engagement
24	Local Relevance	Generic Global Content	Disconnection from community contexts	Localization tools, Community content creation	Hyperlocal environmental education	Importance of local vs global content	AI-assisted content localization
25	Metacognitive Development	Automated Learning Decisions	Reduced self-regulation skills	Explicit metacognitive scaffolding, Learner agency	AI as metacognitive coach	AI impact on self-regulated learning	Agency-preserving AI design
26	Affective Dimensions	Neglect of Emotional Connection	Reduced environmental caring	Affective computing integration, Emotional intelligence development	AI supporting emotional processing	Emotions in environmental learning	Affectively aware educational AI
27	Indigenous Rights	Knowledge Appropriation	Unauthorized use of traditional knowledge	Free, prior, informed consent, Benefit sharing	Indigenous-led AI development	Protocols for indigenous knowledge AI	Sovereignty-respecting AI systems
28	Political Neutrality	Controversial Topic Navigation	Accusations of bias or propaganda	Multiple perspective presentation, Transparent values	Constructive controversy pedagogy	Handling polarizing environmental topics	Balanced discourse facilitation AI
29	Quality Control	Variable Content Accuracy	Misinformation in educational materials	Expert review, Automated fact-checking	Crowdsourced quality assurance	Scalable quality mechanisms	AI-assisted expert review

30	Integration Complexity	Fragmented Tool Ecosystems	Cognitive load, Data silos	Interoperability standards, Unified platforms	Ecosystem approaches	Optimal integration architectures	Seamless educational AI ecosystems

Global collaboration platforms involve students worldwide, regardless of geographical, cultural, and economic borders, to work together in environmental initiatives to create intercultural competence and global citizenship. Online interactions abolish the travel emissions and facilitate relationships that are not possible in the actual study abroad. Problem-solving is done by the members working collectively around the common environmental issues and this generates the perception of divergent views and contexts. The global networks emerged in the course of education aid with the international cooperation over lifelong sustainability.

3.14 Policy and Regulatory clarifications

Active adoption and involvement of AI into green education needs to be supported by favorable policies and the right policies and governance systems that can facilitate the innovations without jeopardizing the safety of students, teachers and communities. The educational technology policies need to focus on the AI-related concerns such as accountability of algorithms, data management, and equity promise as well as on the facilitation of pedagogical creativity and evidence-based refinement. The regulatory rules of data protection in the field of educational AI must set clear parameters on what data should be collected, used, shared and retained about student information. The laws related to student privacy differ significantly based on the jurisdiction at either end of the spectrum to problems with compliance concerning platforms which deal with an international audience. The rules must require meaningful consent, purpose restriction against mission creep, data minimization of only required information, and information on data practices. Sanctions to compliance breach are not to deflate innovation by taking too much risk. The frameworks of algorithmic accountability demand that the operation of the AI systems is transparent, the assessment of bias and discrimination is accurate, the ways of challenging the algorithmic decision are consistently in place, and responsibility is distributed if the AI systems are harmful to students. The requirements of explainability are modeled keeping in strike the significant understanding of the reasoning in a system in equilibrium with assuring the secrecy of proprietary algorithms. The risks in the form of the risks to be mitigated could be detected through mandatory impact assessment prior to the utilization of AI in the educational setting. It is checked by independent auditing to be sure that it is effective and compliant. Accountability structures ought to be commensurate of the risk and impact as opposed to being consonant and visible.

There should be equity mandates because AI-driven green education is meant to benefit all students and not only advantaged ones. The requirements of universal design include support of accessibility at their early stages of development and not retrofitting. Technology is subsidized in poorly resourced schools and communities. AI pedagogical integration is one of the teacher training budgets. Funds on curriculum development favour culturally sensitive, multilingual material. The procurement policies adopted by the government emphasize vendors who undertake equity obligation in terms of designs, accessibility characteristics and show their inclinations to serve various people. Educational AI quality sets minimum demands of effectiveness, safety and suitability. Pedagogical soundness reviews assure that AI application is consistent with learnings sciences as opposed to automating bad practices. The requirements of evidence require causation of learning outcomes in form of rigorous research before the large-scale usage. Risk testing avert psychological damage, breach of privacy or weakness in security. The age appropriateness criteria allow the protection of young children against the developmentally inappropriate content or patterns of interaction. Standards are to be updated along with the progressive research and technology instigated instead of entombing themselves on the existing limits. In the policy of intellectual property, the right to property, the right to authorship, and the right to payment of remuneration regarding AI-generated educational material, student-evaluated AI-aided work, and information obtained as a result of learning activities are discussed. Access and adaptation to publicly funded AI would be the greatest when it is open-licensed. The rights to student data give the students control over their educational records. Attribution requirements allow humanity to have its contribution as well as AI generation. In benefit sharing, societies that contribute to knowledge that has been used in AI systems are paid.

The policies of professional development guarantee educators the competencies of effective and critical integration of AI. Programs of teacher education would have to incorporate AI literacy, pedagogical integration of AI, ethical issues and experience with educational AI tools. Professional development is the way to encourage continuous learning because technologies change. The allocation of time and funds acknowledges the fact that the process of integrating AI will also need extensive work in addition to the ongoing tasks. The teacher voice in AI procurement, implementation and evaluation respects professional expertise and ownership is developed. Research and evaluation policies promote thorough research of the AI educational effects and safeguard the participants as well as promote evidence-based enhancements. The independent research is funded through diverse methods other than the efficacy studies conducted by vendors, which may have conflict of interest. In the situations of educational AI, research ethics frameworks adjusted to correspond the situation desire to weigh innovative approaches and safeguard student participants. Policies of data sharing help in sharing data and safeguarding privacy. Quick cycles of evaluation are in line with the rate of technology evolution but still remains rigorous. Requirements of environmental sustainability of education AI consider not only carbon footprints, resource consumption, and electronic waste of technologies per se. Standards of energy efficiency offer optimizations of AI models and infrastructure. Access to renewable energy will supply data centers with energy requirements to mitigate climate. The sustainability hardware policies prioritize lifetime, repairability and recyclability. Lifecycle assessments indicate trade-offs on the environment and informs the decisions of procurement.

The global collaborative efforts of AI in education can be achieved through the international cooperation frameworks that provide the sharing of knowledge, standard harmonization, and joint efforts on issues of global challenges. Interoperability Technical standards can avoid vendor lock-in and minimise the redundancy of development. Data cross-border structure on mutual understanding of privacy protection, which is critical to international educational structures. Joint research projects combine funds to research issues that are not capable of being addressed in individual nations. The development aid aids elementary AI educational capacity building among resource constrained nations. Ethical oversight measures will serve to give continuous direction, examine disputable situations, and develop norms that will deal with the emerging AI-based education practice. High-risk AI implementations are assessed by ethics committees that comprise educators, students, technologists, as well as community members. Developers are trained in ethics to make them responsible and enlightened. The wider communities are involved in the AI education futures through the processes of public dialogue. The ethical frameworks are regularly re-examined to keep up with the changes in technologies, social values, and scientific knowledge.

4. Conclusions

This literature review gives an overall picture that artificial intelligence is a game changer in green education, that has provided unprecedented opportunities to enhance environmental literacy, climate change knowledge as well as sustainability skills necessary to fulfill the Sustainable Development Goals. The combination of mainstream AI technologies in the form of machine learning systems, natural language processing, computer vision, and intelligent tutoring system with pressing demands to educate about the environment offers the possibility to rethink how communities can develop ecological awareness and relations toward sustainable practices among different population groups and circumstances. The discussion shows impressive scope and level of AI applications in the form of intelligent tutoring systems which deliver personalized environment education, VR environments which encourage learners to experience an ecosystem otherwise not available, computer vision technology that predicts species recognition and environmental surveillance, learning analytics are patterns in knowledge acquisition and interaction, and next generation platforms are those that inspire you to change your behavior towards sustainability through engagements in futuristic settings. These applications mitigate severe constraints of conventional environmental education such as standardization which disregards the divergent learning requirements, lack of interaction with actual environmental facts and phenomena, restricted scaling of the experiential education and inadequate individualization to the levels of personal knowledge and cultural background.

Applications of AI driving these tasks include supervised learning to do classification or reinforcement learning to optimise teaching strategies, natural language processing to do conversational interfaces and generative models to do customized educational content and predictive analytics to do forecasting of learning and multimodal systems that combine both vision and language with sensor data. The complexity of these methods keeps on improving rapidly with the capability of providing more and more powerful educational uses at the same time raising new problems that need prolonged concentration of the researcher, practitioners, and policymakers. However, there is still much to be done with potential developments, as AI-based green education is limited by serious challenges. The digital divide leads to deep inequalities, with the benefits being accumulated with people who are advantaged, and the vulnerable groups that have never had access to these amenities and are highly adversely impacted by environmental degradation are left out. Across training data and model structures, there is the possibility of propagating stereotypes and worsening non-Western knowledge systems due to algorithmic bias within training data and model structure. There exist data privacy issues due to massive data gathering and data analysis about the students. The environmental imprint of AI systems as such is incompatible with the concept of sustainability where energy-consuming computation results in the significant emissions. The pedagogical issues raise the question of whether technology really does contribute to the learning process or it is simply a way of automating the learning process without undergoing enhancement. The preparation of teachers is still not sufficient as far as successful AI integration is concerned. Complex models lack transparency, which leads to lack of trust and accountability.

These issues need complex solutions involving technological innovation, interventions in policies and wisdom as a pedagogue. Federated learning and confidentiality through privacy methods such as differential privacy can be used to customize, as well as maintain sensitive data. More equitable systems are formed by the detection of bias and mitigation based on various training data, algorithmic auditing and participatory design. Green buildings and green infrastructures cut the environmental footprints by consuming less energy. Revisionable AI methods increase clarity and trust. Extensive teacher instruction creates the ability to utilize AI effectively and critically. The aspect of universal design is to make it accessible in terms of abilities and context. Cultural appropriateness and relevance are guaranteed by the community involvement in developing and governance. The prospects of innovation are boundless in the future since the capabilities of AI are becoming more developed, and educational models are changing. Multimodal systems are more generalized systems in which vision, language, speech and sensor information interact. Physical educational agents are created by the embodiment of AI in robotic systems. It is through neuroadaptive systems that monitor the activity of the brain which make it possible to optimize instruction with a high level of precision never before realized. Affective computing identifies and reacts to emotion. Intelligence platforms are collective, whereby there is a pooling of insights among students. Dynamic content creation is made possible through generative AI. Sustainability solutions are designed under the support of augmented creativity tools. Lifelong learning ecosystems unite formal and informal lifelong education. Interdisciplinary studies employ environmental issues to put into context several subjects. The nature of indigenous knowledge integration is dual respectful to both the traditional ecological wisdom and the scientific views. Higher research gaps need to be filled with long-term research in order to develop knowledge and practice. Generalizations of AI methods, teaching practices, and the guidelines of sustainability are not developed. There is little empirical research that supports the long-term implications of intervention in environmental behaviors and competencies, and most of the studies have found short-term knowledge of the intervention. There are limited comparative analyses of the various approaches done to various objectives and population. The literature on equity research which covers aspects of accessibility, cultural responsiveness and digital inclusion is incredibly scarce. Sustainability evaluation of AI technologies in themselves are not given enough attention. The interdisciplinary studies between technical development on the one hand and educational scholarship and environmental psychology, and sustainability science on the other are still scarce. The responsible AI policy frameworks in green education have to be elaborated.

Some of these are areas that should be given priority in future directions. To start with, effective impact evaluation as determined by randomized controlled trials and longitudinal studies should be rigorous to prove causality of drug effect other than correlational analysis and vendor-guided studies which tend to harbor conflict of interest. Secondly, participatory design in the use of teachers, learners and communities guarantee cultural suitability, learning effectiveness and practical application. Third, AI in environmental education contexts should be constructed and implanted through ethical frameworks directly relating to AI. Fourth, cross-disciplinary work of computer scientists, educators, environmental scientists, psychologists, and policymakers can provide global solutions, which cannot be realized in isolationist perspectives of each discipline. Fifth, open educational AI projects maximize accessibility and allow to be adapted to local situations. Sixth, policy development puts in place guard rails to minimize harm to the learners but also encourages good innovation. The applied implementation of AI needs to be moderate in terms of technological advancement and innovation and pedagogical in terms of functionalities that enable an individual to experience genuine elements of environmental education such as affection towards the natural environment, learning through interaction with peers, critical thinking about complicated socio-ecological phenomena, agency, and efficacy formation as environmental citizen. Outdoor experiences and contact with nature are to be promoted with technology instead of replacing screen acts with physical interaction with systems of living. The AI systems should encourage and not erode the teacher expertise, professional judgment and adaptation to the context.

The ultimate purpose of introducing AI in green education is much larger in scope due to the production of environmentally active and sustainably behaving global citizens who are able to overcome challenges never seen on humanity and the biosphere. Education is one of the key leverage points of sustainability transitions that defines knowledge, values, skills, and behaviours to enable societies to move towards prosperous futures or further degradation. AI provides strong means to make environmental education more effective, accessible, engaging, and transformative, and achieving such a potential implies paying close attention to equity, ethics, pedagogy, as well as sustainability itself. With the growing rates of climate change, loss of biodiversity, and strain of limited resources, the need to have better green education becomes urgent. The solutions of AI promise to offer hope to scale the quality environmental learning to the billions of individuals in various settings, tailor to individuals, and situations, and adapt to the fast changing environmental conditions. Nevertheless, technology in itself cannot bring about educational transformation. It takes a long-term investment in infrastructure and content, thorough teacher training, favorable policies and governance, community involvement and ownership, and adherence to equity that will create it a flow to the population that experiences the negative impacts of environmental issues. The review is related to the current scholarship in the AI use in education and environmental education, it is a synthesis of fragmented literature, it determines the areas where investigations are required, as well as potential directions of research and practical implications to stakeholders. The thorough discussion of applications, methods, issues, and opportunities offers grounds to evidence-based development and implementation and call out the areas that have to be addressed immediately. The model between AI functions and learning goals and sustainability performance allows analysing and designing it in a system.

However, in the future, the profession should be able to walk the fine line between excitement over technological potentials and realism about limitations, dangers, and unintended consequences. The world should not be technologically able to do things but through clear educational goals and sustainability values, the world must be encouraged to innovate. The process of development must include a variety of stakeholders that will make sure that AI is developed in accordance with real needs instead of foisting solutions on problems that do not exist. Assessment should determine meaningful outcomes such as long-term behavior change, environmental effects, equity effects and wellbeing as opposed to small objectives such as participation and the test results. The introduction of AI-infused green educational benefits as a contributor to the sustainable development goals is an impressive idea that is believable yet still has to be matched with significant voluntary effort, resources, cooperation, and prudence. The opportunities will increase as challenges will change with the ever-increasing use of

AI technologies. The teaching society should be flexible, judgmental and dedicated towards the basic objectives of developing environmental awareness and sustainable strengths that alone can result in the development of prosperous societies within a bounded planet Earth. By critically designing, thoroughly executing, seeking critique and doing better, AI can end up becoming an influential partner in the crucial endeavor of green education towards sustainability.

Conflict of interest

The author declares no conflicts of interest.

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