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A Review of Artificial Intelligence Across Principal Areas: Potential, Applications and Limitations

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ABSTRACT
Artificial Intelligence (AI) is rapidly transforming a wide array of sectors by enabling data-driven solutions, automating complex processes, and enhancing decision-making capabilities. This review presents an overview of AI's growing role in four key areas: sustainability, education, healthcare, and support for individuals with physical disabilities. In sustainability, AI is being used to model climate change, optimize energy consumption, and promote smart agriculture. In education, intelligent tutoring systems, personalized learning platforms, and Natural Language Processing (NLP)-based tools are helping improve learning outcomes, accessibility, and engagement especially for students with learning challenges. In healthcare, AI enhances clinical decision support, improves diagnostic accuracy through medical imaging and speech analysis, supports robotic and remote surgeries, and advances mental health monitoring via sentiment analysis and NLP. For individuals with physical disabilities, AI-powered assistive technologies including brain-computer interfaces, eye-tracking systems, and smart prosthetics are redefining independence and mobility. While the potential is vast, the paper also addresses critical ethical, social, and technical challenges, including data privacy, algorithmic bias, accessibility, and transparency. By synthesizing recent developments and identifying current limitations, this review aims to offer a balanced perspective on the transformative potential of AI and the considerations necessary to ensure its sustainable and responsible deployment across these sectors.

***Keywords*: Artificial Intelligence, Sustainability, Education, Assistive Technologies, Healthcare, Challenges**

1. INTRODUCTION

Artificial Intelligence (AI) has rapidly transformed industries by enabling automation, data-driven decision-making, and advanced problem-solving. However, as AI systems become more complex, their environmental and ethical impacts have gained increasing attention. At the same time, AI holds enormous potential to drive positive change across a wide range of sectors—including healthcare, education, accessibility for people with disabilities, and sustainable development. The concept of sustainability in AI focuses on developing and deploying AI technologies in ways that minimize energy consumption, reduce carbon footprints, and promote social responsibility. Recent advancements emphasize efficient machine learning models, energy-aware computing, and ethical AI practices to ensure long-term benefits for both technology and society. As AI continues to evolve, it becomes essential to balance innovation with environmental, ethical, and social considerations, making it a more inclusive and responsible tool for the future.

There is a growing trend that seeks to direct the usage of AI for the betterment of society. While this may be conducive to achieving sustainable development goals, it is important to consider the sustainability of developing and operating the AI systems themselves: Aimee Van Wynsberghe [1] has suggested, in her study on the sustainability of AI that sustainable AI is about a controlled development of AI that can be supported by the enviromental resources available to current and future generations. Strubell et al. [2] showed that training a single, deep learning, Natural Language Processing (NLP) model GPU may lead to around 600000 lb of CO_2 emissions. This is comparable to the emissions from five cars over their lifetimes. Google's AlphaGo Zero generated 96 tonnes of CO2 during its 40 day research training period which amounts to approximately 1000 hours of air travel [3, 4]. It is therefore imperative that we weigh the pros and cons of using AI to accelerate sustainable devlopment to identify whether the potential reduction in emissions through the use of AI adequately outweighs the increase in emissions due to the operation of AI systems. Training or tuning an AI/ML model requires a considerable amount of energy and it is being questioned whether the

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energy spent training a neural network might better be allocated to heating a family's home [2]. Sustainable development is a concept that calls for the improvement of living standards without adversely affecting the earth's ecosystems or causing environmental challenges such as deforestation and water and air pollution [5, 6]. It is often seen as a forward-thinking and visionary concept [7], built on three key pillars: economic, social, and environmental sustainability. It not only involves balancing innovation with fair resource distribution but also managing the challenge of meeting the needs of the environment, economy, and society at the same time. A study conducted by Zhenghua Chen et al. [8] explored the environmental sustainability of AI. It was found that with increasing size and complexity of the AI models, the carbon footprint would be that much more significant. AI models are becoming progressively more powerful along with the drastic increase in their model sizes. The computational requirements of AI models have been said to double every 3-4 months which is a faster growth rate than Moore's Law that claims the requirements double every 2 years [9,10]. An effective way that has emerged to develop computationally efficient AI models is "Compressed AI" which requires less computational resources and generates smaller yet more accurate models [11]. The term "sustainability" itself has become a general umbrella term that encompasses a lot of things but doesn't talk about anything particular in great detail. This lack of definition calls for the terms "sustainability" to be questioned in order to establish its relevance in the modern world [12]. AI for Sustainability is often understood in terms of its application—if AI is used to support the UN's Sustainable Development Goals (SDGs), it is considered part of this field [13]. AI can play different roles, such as predicting future trends or actively helping to address challenges. For instance, it can forecast energy demand or optimize renewable energy distribution through smart grids [14, 15]. AI is also used to protect biodiversity [16] and improve transportation systems to reduce environmental impact [17]. These diverse applications show that AI is used in many ways under the same label. Another major issue is that many AI solutions designed for the SDGs do not consider their own environmental footprint. The question is whether AI systems that consume large amounts of energy and resources still be seen as truly sustainable?

AI in education represents a big change towards a more flexible and immersive learning experience. Intelligent tutoring systems, predictive analytics, tailored learning environments, and administrative support tools are a few examples of AI applications in higher education [18]. The application AI in the field of education is one that is said to tackle a variety of issues in education including enhancement of student retention and engagement, streamlining grading procedures and promoting individualized, tailor-made learning material [19]. AI-driven systems that have this capability to adjust and deliver material based on learning styles and preferences are called personalized learning environments [20]. Makhambetova et al. [21] have suggested that personalized learning can significantly enhance student engagement as well as academic performance. In addition to the most obvious advantages of incorporating AI in education, there are other benefits that also have a profound impact on the overall quality of learning. One such benefit is workload reduction for faculty and teachers. Using AI to complete mundane administrative tasks like grading answer sheets, scheduling classes and other work of a similar nature can allow them to focus on what really matters: providing high quality education. In this respect, Kumar et al. [22] have asserted that automation has the potential improve learning outcomes as a whole.

The number of students with learning disabilities worldwide is 79.2 million and constantly on the rise [23]. Learning disabilities are said to impact children's listening, thinking, speaking, scientific reasoning, reading, writing, spelling, or math and has created substantial needs for special education [24]. Challenges with reading, writing or math reasoning means that these students are provided with fewer learning opportunities than their peers as evidenced by their consistently lower scores in reading, science, math and other subjects [25]. AI has been in use to support students with learning disabilities for many years. Drigas et al. [26] reported in their study that AI can be used to diagnose dyslexia and even symptoms like low attention spans. Similarly, multiple other studies have highlighted the potential of AI in diagnosing or screening for learning disabilities [27-29]. Research has shown that students with some form of learning disability are more likely to experience negative emotions such as depression and loneliness. AI has the potential to make life easier for such students and also have a positive impact on their overall academic performance. There are, however some fundamental problems with the worldwide implementation of AI in the education sector. A recent study conducted by Markus Christen et al. [30] explored the ethical concerns and possible risks of using AI to assist students with learning disabilities. It identified a lack of ethical reflection on the use of AI and an absence of discussion and inclusion of students with disabilities. One of the main concerns highlighted in some studies is the lack of transparency that is associated with AI driven decisions [31, 32]. Others have warned against inherent biases in AI algorithms originating from a lack of data diversity [33-35]. Moreover, the incorporation of AI into an existing ecosystem requires the training of staff to ensure a smooth transition [36]. Last, and perhaps the most fundamental

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concern is resistance from the students and stafff alike stemming from a lack of trust in the accuracy and fairness of AI driven systems [36].

Apart from learning disabilities, AI can be used to tackle other disabilities which are of a more physical nature as well. Assistive Technologies (AT) are those devices which facilitate greater functional independence for people with physical disabilities. Integrating AI with various agents including robotics, electronics and software has resulted in groundbreaking advances in AT's such as bionic limbs, intelligent wheelchairs and smart home assistants [37]. More than a billion people or roughly 15% of the global population live with a disability [38]. This number is only expected to rise due to aging and changes in the incidence of chronic health problems. Mobility aids such as crutches, wheelchairs, prosthetic limbs and specialized home automation software are some of the most common AT's used by physically disabled people [39]. In prosthetics, AI is used to physiologically identify the user's intentions using past data and then robotic actuators can be used to perform the required motion. AI also has the ability to quantify sensory touch/ input and this knowledge can be used to convey somatosensory signals to the brain [40]. AI enabled prosthetic limbs using a variety of biosensors such as force-sensitive resistors (FSR's), electromyograms (EMG's) and mechanomyograms (MMG's) [41, 42]. Brain-computer interface (BCI) technology helps decode human intent from brain signals (such as those obtained by eletroencephalograms and electrocorticograms). This decoded intent is used to control various AT's [43]. Lower limb prosthetics which are AI supported can help overcome or adapt to changing walking environments much quicker than those which are not AI enabled [44]. AI can also allow for exoskeletons to perform different tasks like climbing stairs and avoiding obstacles. They employ AI to detect the wearer's gait and control a robotic system to adjust accordingly. Such exoskeletons are used to provide the wearer with additional force to perform a particular task that they are unable to generate themselves owing to some disability [45]. This is done by AI which estimates the required force to perform that function through sensory input. Camera-based exoskeletons are being explored by several researchers wherein the integrated AI analyzes real time images to determine the best possible response to external stimuli [46]. Similarly, an AI enabled wheelchair uses sensors to perceive and respond to the environment it is in. Sensory data is analyzed by AI to independently choose the best course of action [47]. Various other advancements in this field such as Computer Vision, Natural Language Processing (NLP), Virtual Reality (VR) and Augmented Reality (AR) allow for new ways for users to interact with this technology.

While the use of AI to improve the quality of life for physically disabled people is a fast growing field and holds a lot of potential, there are certain factors or concerns that need to be studied. The primary concern with any AI based device lies with its accuracy. It is imperative that the assistive devices not only perform the task they're designed to do but also ensure that it is done in a safe manner that does not end up harming the user which is counter intuitive. Trustworthy and reliable AI is based on three pillars: they should be lawful, ethical and robust. All these components should be used or "work in harmony and overlap in their operations" and at this would follow the "foundational values of respect for human rights, democracy and the rule of law" [48]. There is no doubt that AI can have a positive impact on the society but considering how the lawfulness and ethics of trustworthy AI can be applied in a situation in which a disabled person needs assistive technology to participate in society as a contributing member raises several questions. Especially when we consider economic and social rights [49].

AI in healthcare is one of the fastest growing sectors with a global compound annual growth rate of 28% and a very high market potential as mentioned by Keijo Haataja et al. in their review [50]. The healthcare industry has been undergoing a drastic transition since 2020. Technology in healthcare has shifted focus to medical solutions that deliver intelligent solutions for evidence and outcome based health where emphasis is on collaborative and preventative care. Robotics, Virtual Reality, Augmented Reality and AI are said to hold the keys to achieving this [51]. A study by M Collier et al. [52] revealed the annual savings potential by implementing AI systems in healthcare to be $150 billion by 2026 in the US alone which should serve as an incentive to accelerate the growth of AI in the healthcare sector. AI applications in healthcare can be classified to the following domains: surgery, nursing assistant, medical consultation, administration and workflow, treatment design, cybersecurity, machine vision, automatic and preliminary diagnosis, health monitoring, medication management, and clinical trials. All these domains have applications utilizing AI in their operations [50].

AI will continue its upward trajectory and ultimately become an indispensable tool for the healthcare sector. There are, however, some concerns regarding data security and privacy. Health records are important and vulnerable, which makes them appealing targets for hackers during data breaches. The absence of standard operational guidelines for the use of AI and ML in healthcare has only served to worsen the situation. There is an ongoing debate about how far artificial intelligence (AI) may be utilized ethically in healthcare settings since there are no universal guidelines for its use [53]. A major problem with AI is that it has become so advanced that the behaviour of AI systems have become increasingly black-boxed which makes them difficult to understand by those that use them and sometimes even those that build them [54]. The lack of critical thinking in AI and the high cost of data collection are some other important drawbacks [55, 56]. MY Shaheen [57] has listed three fundamental problems with implementing AI in healthcare: 1) AI models can reflect existing biases and inequalities present in the healthcare system. 2) The need for large datasets may lead to concerns about patient privacy and data confidentiality. 3) AI systems are not always accurate and can sometimes make mistakes that harm patients or cause other healthcare issues.

In conclusion, this paper provides a comprehensive review of the advancements, opportunities, and challenges associated with the application of Artificial Intelligence in sustainability, healthcare, education, and support for people with disabilities. The purpose of this review is to recognize and analyze the transformative potential of AI in these critical areas, while also acknowledging the ethical, technical, and societal issues that must be addressed to ensure responsible development. By examining both the benefits and the limitations, this paper aims to offer a balanced perspective that encourages the thoughtful integration of AI into systems that prioritize equity, privacy, and long-term sustainability. As AI continues to evolve, it is essential that its implementation across these sectors be guided by principles that maximize positive impact while minimizing harm.

2. REVIEW METHODOLOGY

2.1 Selection of Primary Areas to Review

This review adopts a narrative methodology aimed at providing a clear and accessible overview of the role of Artificial Intelligence (AI) across four critical sectors: sustainability, education, healthcare, and support for individuals with physical disabilities. These sectors were chosen based on their global relevance, the potential impact of AI within them, and the ongoing research and innovation seen in these areas. By narrowing the focus to these four domains, the review aims to explore a broad yet manageable cross-section of AI applications that are socially significant and technically diverse.

2.2 Identification of Pertinent Literature

To ensure that the information included is both relevant and up-to-date, a wide range of academic databases and institutional sources were consulted, including Google Scholar, PubMed, IEEE Xplore, ScienceDirect, and official publications from global organizations such as the WHO, UNESCO, and WIPO. Search terms were tailored to each sector—for instance, using combinations like “AI in education,” “AI for sustainable development,” “AI in healthcare,” and “AI for physical disabilities.” Most of the references selected for this study fall within the time range of 2015 to 2025, with only a few exceptions where earlier foundational works were deemed critical for context or completeness.

2.3 Synthesis and Simplification of Information

Once the relevant literature was gathered, the process of condensing and synthesizing the information began. The focus was on distilling insights from a large body of complex research into simple, coherent summaries that remain accessible to readers from various backgrounds. Emphasis was placed on highlighting core applications of AI, key benefits, common challenges, and ethical considerations relevant to each domain. The goal was not to exhaustively cover every piece of literature available, but to present a balanced and representative view of how AI is currently being used, the promise it holds, and the areas where further development or caution is necessary.

3. AI FOR SUSTAINABILITY AND THE SUSTAINABILITY OF AI

3.1 Compressed AI Models

As concluded by multiple studies, the computational requirements of AI and AI based systems are prohibitively high. This is one of the main reasons experts question whether AI truly supports sustainability or potentially undermines it. There are three major techniques that have gained major prominence in the development of Compressed AI models namely: pruning, quantization and knowledge distillation. As mentioned earlier, compressed AI models are an effective way to develop computationally efficient AI models which require less computational resources and generate smaller yet more accurate models [11].

Pruning helps make AI models smaller and faster by removing unnecessary parts, like weak or unused connections in the network. This reduces memory use and speeds up computation during model use [58, 59]. A simple method is to remove weights with small values, known as magnitude-based pruning [60]. Some approaches use regularization to encourage the model to become sparse during training [61]. While these methods can create irregular structures that are harder to run efficiently, structured pruning solves this by removing whole filters or layers, which work better on standard hardware [62]. Other techniques remove neurons that don't activate much—like those producing zeros after functions such as ReLU [63]. Although pruning can save resources, it sometimes requires retraining the model to keep accuracy high [64, 65]. Newer methods try to avoid this by pruning at the start [66] or training with built-in sparsity [67].

Quantization is a method used to reduce the size and speed up AI models by lowering the precision of numbers used in the model. For example, instead of using 32-bit floating-point numbers, the model can use 16-bit, 8-bit, or even 1-bit values [68, 69]. This not only cuts down storage space but also makes the model run faster, especially on devices with limited resources. Some techniques convert model weights into power-of-two values, allowing faster operations using bit shifts instead of multiplications [70]. Others reduce the precision of gradients during training to save resources [71]. Combining quantization with pruning often leads to even better results in compressing models [72]. However, this approach usually works best when the model structure stays the same.

Knowledge distillation is a technique where a smaller model (student) learns from a larger, well-performing model (teacher). This helps the smaller model achieve good results while being faster and more efficient [73, 74]. The student can learn from the teacher's final outputs (called logits), features from hidden layers [75], or relationships like attention patterns [76]. Some methods use multiple teacher models to give the student a broader understanding [77], while others let a model learn from its earlier version—this is called self-distillation [78]. Although KD is flexible and works across different model types, it often requires extra effort to train both teacher and student models. A good solution is to reuse pre-trained models as teachers, which saves time and supports sustainable AI development [79].

In recent years, there has been increasing focus on the sustainability of AI, particularly its environmental impact. Researchers such as Strubell, Brevini, and Coeckelbergh have raised concerns about AI's resource consumption from different perspectives. Strubell et al. [80], Lacoste et al. [81], and Dodge et al. [82] have analyzed the energy usage of AI systems, especially in machine learning (ML) and natural language processing (NLP). Meanwhile, Crawford and Joler [83] take a broader view, studying the entire lifecycle of AI systems, from resource extraction to workforce conditions and user interactions, to better understand their sustainability challenges.

Additionally, AI for Sustainability and AI for the UN's Sustainable Development Goals (SDGs) have become central topics in global AI ethics discussions. Experts like Floridi have explored how AI can be used to address environmental and social challenges [84]. Coeckelbergh emphasizes the need for responsible AI applications to support climate action and sustainability efforts [85]. Floridi et al. [85] propose an ethical framework that examines how AI can contribute to solving complex global issues, laying the groundwork for what they call a "Good AI society." They argue that AI, when used to support human intelligence, has the potential to significantly enhance human decision-making and problem-solving.

For example, AI tools in agriculture or energy management are typically classified under AI for Sustainability. However, this definition is quite broad and does not guarantee that AI truly contributes to sustainability.

3.2 Integration of AI with IoT to Enhance Environmental Management for Sustainability

Irmina Durlik et al. [86] explored the integration of AI agents and IoT (Internet of Things). This advancement has marked a pronounced shift in environmental monitoring and management owing to enhanced data gathering facilitating in-depth analysis and accurate decision making. Conventional monitoring methods require intermittent data collection and manual analysis are fast becoming insufficient and obsolete. Monitoring of rapidly changing environmental conditions requires an equally fast and adaptable system of data acquisition and analysis. IoT has become a key development in this regard, allowing data collection from a wide array of interconnected sensors and devices to facilitate continuous monitoring of diverse environmental parameters [87-89]. Parameters such as air and water quality, temperature, humidity, and soil moisture can be monitored by IoT and the corresponding readings can be transmitted to the central system [90]. AI also plays a major role in forecasting and environment related predictions. Machine learning algorithms can identify patterns, predict trends, and derive actionable insights from complex environmental data, thereby enhancing decision-making processes [91-93]. AI-driven models are capable of forecasting pollution levels, anticipating climate anomalies, and optimizing resource management strategies, allowing environmental scientists and policymakers to respond more swiftly and effectively to emerging challenges. The integration of IoT and AI creates a synergistic framework that leverages the strengths of both technologies [94]. While IoT provides a continuous stream of extensive environmental data, AI offers the analytical tools to transform this raw information into meaningful insights. Together, they enable faster and more accurate decision-making, thereby significantly enhancing environmental monitoring, management, and sustainability initiatives.

3.3 Some Real-World Applications of AI for Sustainability
AI systems have been used extensively across diverse applications with the primary aim of ensuring sustainable environmental practices and habits. Their applications extend to resource management, biodiversity conservation, urban planning [95], emissions forecasting [96], and advanced robotics, underscoring the versatility and growing impact of AI in environmental science. In the Great Lakes region, an AI-powered water quality monitoring system [97] employs IoT sensors to continuously measure key parameters such as pH, turbidity, dissolved oxygen, and contaminant levels. AI algorithms process this data in real time, enabling the detection of pollution events and the prediction of future water quality trends. This integrated approach has significantly improved proactive water management, allowing for more effective mitigation of pollution-related challenges. Biodiversity preservation has also been enhanced through the integration of AI technologies [98, 99]. AI-powered drones and camera traps are increasingly used for wildlife monitoring, enabling the detection of potential threats and supporting targeted conservation efforts [100]. Machine learning models are also used to assess ecosystem health, helping develop sustainable strategies to protect biodiversity [101]. However, using AI in conservation brings ethical and cybersecurity challenges that must be addressed to ensure responsible use and safeguard sensitive environmental data. AI has also driven major progress in urban planning and green building technologies [102]. In cities, AI systems analyze data on population density, land use, and infrastructure to support more sustainable urban development. Machine learning is used to design energy-efficient buildings, helping reduce resource use and cut carbon emissions [103]. AI also manages indoor environments by controlling air quality, temperature, and lighting, ensuring healthier and more efficient spaces. These technologies are key to building smart cities that combine sustainability with improved quality of life [104, 105]. Additionally, AI plays a vital role in forecasting CO_2 emissions [106]. For example, the biogeography-based optimization (BBO) algorithm has been applied to model emission trends, giving policymakers the data needed to shape effective environmental policies and strategies [107].

3.4 Sustainability of AI From an Energy Standpoint
As outlined by the UN, AI holds significant potential to address several global challenges [108]. Some of these problems include: prediction of energy consumption, optimizing energy systems and integrating renewable energy sources [109, 110], Improving the energy efficiency of buildings and industrial infrastructure, optimizing the operation of energy systems in real time [111-114], AI can improve the efficiency of renewable energy sources, such as wind and solar energy [111-114] which is particularly important in the decarbonization process [115]. However, rapid growth in AI based technology has seen a substantial increase in energy consumption particularly in Large Language Model (LLM) training [116]. Tech giants such as Google, ,Microsoft and OpenAI are facing a very steep climb ahead of them in their bid to reach carbon neutrality by 2030 [117, 118]. The energy efficiency and consumption of a building under different climatic conditions can accurately be predicted through a combination of AI and physical simulation which not only leads to increased efficiency of energy utilisation but also optimal indoor comfort [119]. A major challenge in sustainable building research is applying machine learning (ML) and multi-criteria optimization methods to improve energy efficiency and lower carbon emissions—especially in the face of climate change and rapid urbanization. In recent years, artificial intelligence (AI) and optimization techniques have been widely used to develop models that predict and optimize energy use, particularly in urban areas impacted by the urban heat island (UHI) effect and changing climate conditions [120]. S Alawadi et al. [121] emphasised the importance of employing neural networks to model HVAC (heating, ventilation and air conditioning) systems to enhance comfort and energy efficiency in buildings. Manapragada et al. [122] provide insisghts into the possible creation of sustainable urban environments that are capable of withstanding climate change by applying ML models in the design of energy efficient structures and weather forecasting. Furthermore, Sha et al. [123] examine mechanical cooling in high-rise buildings and show that using machine learning to model climate conditions can improve the efficiency of ventilation systems and lead to significant energy savings. Similarly, Fathi et al. [124] highlight the strong potential of AI to handle changing climate scenarios by predicting future energy demands and helping buildings adapt to evolving environmental conditions. Special focus is placed on optimizing heat transfer and improving indoor comfort. Advanced machine learning techniques, such as CNN-LSTM models, have proven effective in simulating a building’s thermal behavior and optimizing HVAC system performance, leading to energy savings ranging from 15.7% to 22.3% [125]. It was concluded in the study conducted by Scola et al. [126] that a sector’s energy efficiency is directly

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proportional to the number of AI and IoT devices that were deployed. A study [127] explored the use of AI and thermography to assess heat loss through building envelopes. By combining drones with infrared cameras, researchers were able to detect specific areas of heat loss, helping to design targeted strategies for improving energy efficiency. In another study, Mircoli et al. [128] applied machine learning algorithms to evaluate the thermophysical performance of ventilated facades (VFs) and predict heat fluxes. This work highlights the importance of machine learning in modeling how buildings respond to different temperature and structural conditions, ultimately aiding the creation of more accurate and adaptive energy consumption models. A major challenge in sustainable development is the significant impact of buildings on global energy use and greenhouse gas emissions. Buildings are responsible for up to 50% of global energy consumption and about 30% of greenhouse gas emissions, emphasizing the urgent need to improve their energy efficiency to meet sustainability goals [129]. The use of artificial intelligence and machine learning to predict and enhance energy efficiency—both at individual building and city-wide levels—has become a key strategy in addressing this issue. Research shows that accurate energy consumption predictions must consider factors like climate change and building functionality [130]. One important innovation in this area is the use of AI and cloud technologies to automate energy management, often using time series data [131]. These systems not only optimize energy use but also detect anomalies and generate customized reports for stakeholders [132], contributing to more efficient energy utilization and lower carbon emissions [133].

4. IMPLEMENTATION POTENTIAL AND FEASIBILITY OF AI IN EDUCATION

4.1 Working of AI in Education

With the help of AI platforms, instructors can now perform various administrative tasks such as grading and reviewing assignments more efficiently and accurately, allowing them to focus more on the quality of their teaching. Additionally, because these systems use machine learning and adaptive technologies, they can personalize curriculum and content to match individual student needs. This personalization has led to improved engagement, better retention, and an overall enhancement in the learning experience and outcomes [134]. In the past, educators carried stacks of handwritten assignments, spending hours manually reviewing content, checking grammar, and attempting, often unsuccessfully, to detect instances of plagiarism. Fast forward to the present day, and the landscape has changed dramatically. With the help of artificial intelligence, educators can now automatically assess grammar, detect plagiarism with high accuracy, and even provide personalized feedback. Digital platforms have also enabled remote teaching, allowing instructors to manage their responsibilities efficiently from virtually anywhere. The advancement and integration of AI technologies have significantly reduced the administrative burden on educators, enabling them to focus more on teaching quality and student engagement. Numerous studies have explored the use of cobots or the application of robots, working together with teachers or colleague robots (cobots) which are being applied to teach children routine tasks, including spelling and pronunciation and adjusting to the students' abilities [135-137]. Similarly, web-based and online education has evolved significantly. Initially focused on simply providing downloadable materials for students to study and complete assignments, it has now progressed to include intelligent and adaptive systems. These systems learn from both instructor and student behavior to dynamically adjust content and delivery, ultimately enhancing the overall learning experience [138-141]. AI systems in education use various techniques such as machine learning, data mining, and knowledge modeling—for learning analysis, recommendations, and knowledge acquisition [142]. These systems typically include teaching content, data, and intelligent algorithms, and are made up of two main components: system models (which include learner, teaching, and knowledge models) and intelligent technologies [143]. Models help create a structured data map, establishing associations within educational data to enhance learning outcomes [144]. These models form the core of AI systems, while intelligent technologies provide the necessary computational power. Educational data mining is a process that focuses on generating systematic and automated feedback for learners. When combined with AI, it aims to uncover underlying patterns and deliver personalized learning content based on individual needs. For example, a student's demographic information and performance data can be analyzed even from a limited number of assignments—to provide tailored educational support [144]. Data mining, in other words can be seen as pattern discovery. One key application of data mining-based AI is personalized learning, where students learn at their own pace and choose methods that suit their preferences, guided by AI. Ideally, learners can focus on topics of interest, while instructors adapt the course content and teaching style accordingly [143]. By leveraging data mining and machine learning, AI systems can better understand student behavior and needs, leading to more accurate insights and reliable learning outcomes. Machine learning, learning analytics, and data mining are closely related technologies for education. They share similar goals

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and techniques, drawing from disciplines like machine learning, data mining, statistics, psychometrics, and data modeling [145]. Learning analytics tends to focus on managing learning content and analyzing large-scale assessment data, while educational data mining originates from intelligent tutoring systems and often works on smaller, more detailed cognitive processes.

4.2 Role of AI in Education

Studies show that AI has been applied in the education sector in a number of different ways: one of them being in the form of the automation of repetitive administrative tasks and duties like grading, providing feedback on assignments and content development. This shift has allowed educators to focus on delivering high-quality lectures to the best of their ability while still having ample time outside of their professional life to engage in personal endeavours. These tasks can be carried out through web-based platforms or computer programs. AI has also made remote learning a viable alternative if in-person learning is not possible owing to unforeseen circumstances. Video conferencing and audiovisual files have been enriched by AI to provide a seamless remote learning experience that is tailored to the student's learning style. The rapid growth of web-based platforms, robotics, virtual reality and 3-D technology has enhanced the overall effectiveness of educators and their ability to get through to the students. The application of AI in education offers the opportunity to overcome physical barriers, including national and international borders. With learning materials now hosted online, students can access content from anywhere in the world. AI tools like real-time language translation further enhance accessibility, allowing learners to engage with educational content in ways that suit their individual needs and abilities.

4.3 Real-World Applications of AI in the Education Sector

AI has enhanced efficiencies in institutional and administrative services [146]. Rus et al. [147] noted that Intelligent Tutoring Systems (ITSs) can perform various functions, such as grading assignments and providing students with personalized feedback on their work. Instructors who use Intelligent Tutoring Systems (ITS) can improve efficiency in administrative tasks while also enhancing their core role of guiding and supporting students in their learning. Mikropoulos et al. [148] concluded in their study that leveraging and using AI in education has fostered effectiveness and efficiency in the performance of administrative tasks, such as grading of students' assignments. Today's online learning environments are supported by AI-powered tools like Turnitin and Ecree, which assist instructors by automating tasks such as plagiarism detection and providing guided feedback. These technologies streamline time-consuming administrative duties, allowing educators to focus more on teaching and student engagement. Without AI, such tasks would require considerably more time and effort to complete manually. Timms [135] has highlighted several ways AI is used as a teaching aid, including simulation-based instruction that leverages technologies like virtual reality. These tools allow students to engage with concepts in a more immersive and hands-on manner, offering practical, experience-driven learning opportunities. Keeping medical education in mind, Wartman et al. [149] highlighted virtual reality and simulation, which allows medical students to explore practical aspects of their training, such as performing simulated surgeries and studying human anatomy, among other key areas. Sharma et al. [146] noted that integrating AI into education, especially alongside other technologies has led to the creation of more effective teaching tools. Similarly, Pokrivcakova [150] emphasized the use of AI in computer programs, particularly the development of chatbots that can answer common student questions and, in some cases, deliver instructional content. AI gives humanoid and other types of robots cognitive, decision-making, and conversational abilities, allowing them to serve as effective instructional and teaching tools. Peredo et al. [151] discuss Intelligent and Adaptive Web-Based Education (IWBE) systems, where teachers are seen as key social agents. These systems aim to understand and support teachers in delivering instructions and guidance to students. Moreover, according to Luckin et al. [152] predictive analytics which has the ability to examine student data and forecast certain outcomes can significantly reduce the risk of dropout and bring about an increase in course completion rates. The goal is to ensure that web-based education is used efficiently and systematically to enhance the overall learning experience. The integration and use of AI in education has primarily aimed to enhance the learning experience, while also significantly impacting various other aspects of the educational process.

4.4 Role of AI in Assisting Students with Learning Disabilities

Disorders with onset in childhood or adolescence encompass neurodevelopmental disorders (NDDs), such as autism spectrum disorder (ASD), dyslexia, and attention deficit hyperactivity disorder (ADHD), as well as a wide range of mental health disorders (MHDs), including anxiety, depression, stress-related conditions, and psychotic disorders. Notably, there is a high rate of co-morbidity between NDDs and MHDs [153]. Students with these disorders struggle to cope with and adapt to the ever-changing environment around them and, as a result are at a disadvantage compared with other learners their age. Children with ADHD find it difficult to maintain sustained attention, can be hyperactive, fidget and find it difficult to participate in turn taking [154]. Dyslexia, a common neurodevelopmental disorder and learning disability, affects 3–15% of school-aged children [155]. It is marked by specific impairments in developing expert reading skills, characterized by difficulties in accurate or fluent word recognition, spelling, and decoding [156]. Functional brain imaging studies have revealed differences in brain activity between individuals with dyslexia and those without the condition. Autism spectrum disorders (ASDs) are characterized by difficulties in social interaction [157, 158], speech and language delays, avoidance of eye contact, challenges with adapting to environmental changes, repetitive behaviors, and unique learning profiles [159]. Both children and adults with ASD also experience high rates of anxiety and depression. Yoro et al. [160] highlighted the need for personalized support systems for these children to assist them with their learning. Personalized assistive educational tools could significantly enhance educational outcomes for individuals with neurodevelopmental disorders. These tools can promote better societal integration, reduce stigma and isolation, and mitigate stressors such as bullying, which are known to be common triggers for suicide attempts [161]. A number of AI based tools/ systems have been developed to function as personal assistance providers for these children. Some studies [162, 163] highlighted the use of a tool called *DytectiveU,* a digital application designed to enhance the learning experience of dyslexic students: it offers students a variety of actions that help them with reading and writing. Another educational software called *Squizzy* functions as an assistive technology that helps students stay focused during activities that involve cognition such as pattern or colour recognition [164]. A digital application called *Life Skills Winner* which employs deep learning/ machine learning algorithms serves to teach students daily living skills [165]. Muharib et al. highlighted a digital application that helped enhance social skills called *Facesay.* Rice et al. [166] confirmed the app's great potential as a cost-effective and efficient tool for teaching affect recognition and mentalizing skills to high-functioning students with ASD. The *Kaspar* robot helped improve learners' social and interpersonal skills as concluded by numerous studies [167, 168]. Papakostas et al. [169] emphasised the robot's human like body and features as playing a massive role in getting students with ASD to be more interactive. AI thus provides great relief to students with these disabilities and ensures that they are not at a disadvantage in their respective learning environments which goes a long way in not just ensuring they receive the best possible education but also ensuring that they are happy in their surroundings.

5. AI IN ENHANCING THE LIVES OF PEOPLE WITH PHYSICAL DISABILITIES

5.1 Potential of AI in Assisting People with Physical Disabilities

Artificial intelligence (AI)-driven solutions hold significant potential to support individuals with disabilities by assisting with daily activities and even enabling the development of new skills [170]. Artificial intelligence (AI) is revolutionizing the way we manage daily tasks, offering innovative and efficient solutions. By automating processes such as speech recognition, visual perception, predictive text, and decision-making, AI simplifies tasks typically requiring human intelligence. For individuals with disabilities, this technology has the potential to greatly improve mobility and enable greater participation in everyday life. The quality of life for persons with disabilities (PwD) is often severely impacted, making even simple daily tasks challenging. Difficulties in communication and independent living further hinder their well-being. The integration of machine computational power with human perception and intelligence, known as AI, offers tools to reduce many of the barriers PwD face in their everyday lives [171]. AI also holds the potential to enable education and employment opportunities for PwD in a dignified and empowering manner [172].

5.2 AI Solutions for the Hearing Impaired

Deaf individuals face significantly higher rates of mental health issues than the general population, primarily due to communication challenges and social isolation [173]. Their exclusion is further intensified by limited access to essential services such as education, employment, and healthcare [174, 175]. The criminal justice system also poses unique obstacles for Deaf individuals with mental health needs, compounding their difficulties [176]. Researchers emphasize the need to eliminate communication barriers as a critical step in empowering and supporting the Deaf community [177]. There are various AI projects that have been created keeping communication in mind. *DeepSign* is a cutting-edge initiative that leverages deep learning techniques to detect and recognize sign language [178]. The project focuses on enhancing communication between Deaf and hearing individuals by accurately identifying isolated gestures in Indian Sign Language (ISL). *SignGAN* is a another project designed keeping communication in mind. It

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can translate spoken language into photo-realistic sign language videos [179] and is the first end-to-end model capable of generating high-quality, continuous sign language videos directly from text input. Hu et al. [180] provided a detailed account of *SignBERT*, an innovative project focused on advancing sign language recognition (SLR) using self-supervised pre-training and hand-model-aware representations. It is the first self-supervised framework for SLR that integrates prior knowledge about hand movements. Fang et al. [181] talked about *SignLLM*, a pioneering project which introduced the first extensive multilingual sign language dataset alongside the first large-scale multilingual Sign Language Production (SLP) model, marking a significant advancement in sign language research and technology. A sign language translator called *Migam.ai* shows great promise in having the ability to bridge the gap between sign language and spoken language and represents a significant leap in assistive technology. Migam.ai is built on a robust AI architecture that integrates advanced technologies to bridge linguistic and visual aspects of sign language. It utilizes BERT for natural language understanding, GPT for language generation, and VQ-VAE (Vector Quantized Variational Autoencoder) to efficiently encode sign language features. This innovative combination enables a deep and nuanced approach to sign language interpretation and synthesis [182]. Additionally, smartphone virtual assistants offer speech-to-text conversion, keeping individuals connected to those around them. *Ava* transcribes conversations using AI, enabling users to follow discussions without relying on lip-reading [183]. *Otter.ai* provides real-time voice transcription, converting speech into text, which can also benefit individuals with mobility impairments or dysgraphia [184]. *Google Live Transcribe* offers similar functionality, converting conversations to text in real time, with an added offline mode to assist users even without internet access [185]. AI thus empowers hearing impaired individuals by breaking communication barriers through tools like real-time transcription, sign language recognition, and text-to-speech technologies. These innovations enhance accessibility, enabling greater participation in education, work, and social interactions.

5.3 AI Solutions for the Visually Impaired

Visually Impaired individuals face numerous challenges in their daily lives, often stemming from barriers in accessibility and inclusion. Navigating physical environments without visual cues can be difficult and may lead to safety concerns. Limited access to information in visual formats, such as printed text or digital content without assistive technologies, can hinder education and employment opportunities. Social interactions may also be impacted due to nonverbal communication cues being inaccessible. These obstacles can contribute to feelings of isolation, emphasizing the need for inclusive solutions to promote independence and equal participation in society. AI-powered tools significantly enhance accessibility for visually impaired individuals by simplifying device navigation and improving daily interactions. VoiceOver (iOS) and TalkBack (Android) are built-in screen readers that use AI to describe text, app icons, and battery levels [186, 187]. Siri and Google Assistant assist with smartphone functions and communication [188, 189], while Cortana, a Microsoft virtual assistant for desktops and laptops, enables voice-guided navigation [190]. Additionally, Google's Lookout leverages phone cameras to identify and announce objects, currency notes, labels, and signage, further supporting independent living [191]. With the rapid development of AI technology, it has become possible to integrate AI technologies into VR (virtual reality) systems to enhance accessibility for individuals with visual impairments [192]. *SeeingVR*, created by Zhao et al. [193], introduces a suite of 14 tools specifically designed to make virtual reality more accessible for individuals with low vision. Among these, three tools harness AI technology: edge enhancement for better object detection, text-to-speech for reading on-screen text, and audio scene descriptions to convey visual scenes through sound. Testing with 11 participants with low vision revealed that *SeeingVR* significantly improved their ability to complete tasks and enhanced their overall VR experience. Polys et al. [194] developed audio captioning algorithms aimed at improving accessibility for 3D content on the web. They conducted a user study with 44 participants to assess the algorithms' effectiveness in search and summary tasks. The results indicated that the algorithms performed variably depending on the task, emphasizing the importance of selecting the right algorithm to enhance accessibility for individuals with visual impairments in virtual environments. Rasla et al. [195] explored obstacle avoidance and object selection in virtual reality using simulated prosthetic vision. They tested different scene simplification modes: DepthOnly, EdgesOnly, EdgesAndDepth, and EdgesOrDepth. Participants achieved the highest success rate for obstacle avoidance with the EdgesAndDepth mode (89.8%) and completed tasks fastest with DepthOnly (17s). For object selection, DepthOnly and EdgesOrDepth were most effective. Kim [196] developed a deep learning-based algorithm for Braille block recognition using a VR white cane. The system provides feedback through vibration and sound to assist users in navigating virtual environments, identifying Braille blocks through image inputs using a decision-making model.

5.4 AI Solutions for People with Disabilities that Affect Mobility

Microsoft's AI for Accessibility program uses AI to address physical and cognitive challenges faced by individuals with disabilities, aiming to enhance their autonomy in areas like employment, daily activities, and communication [197]. Google's map services help people with disabilities gain more independence while traveling by offering features such as trip planning, transportation options, and wheelchair-accessible routes [198]. Autonomous self-driving cars, integrated with AI technologies like virtual assistants and map features, will further improve mobility for people with disabilities by providing greater independence and access to their surroundings [199]. Additionally, robotic mobility aids, such as those in public spaces, can assist with navigation and act as virtual assistants, often integrated with wheelchairs. Wearable devices, like smartwatches, offer real-time navigation with haptic feedback, helping users navigate without visually engaging with a screen. The global amputation rate is estimated at around one million per year [200], with the most common causes being severe injuries, muscle tumors, infections, and uncontrolled nerve tissue growth [201]. AI has significantly contributed to making prosthetic devices more realistic, like human limbs. AI, a data-driven methodology, can be enhanced by collecting physiological data through biosensors like EEG [202], EMG [203], and electrooculography (EOG) [204], along with physical signals such as MMG [205], inertial measurement units (IMUs) [206], and FMG [207]. One study demonstrated that using physiological signals from both amputated and non-amputated lower limbs to predict user intent significantly reduced classification errors [208]. Current AI-enabled prostheses, such as the Ottobock bebionic hands and the Össur i-Limb Ultra, are capable of only a limited number of grasp patterns [209]. These prostheses rely on EMG signals from flexor and extensor muscles, and the user may drive a single DoF, such as opening and closing. Several AI algorithms have been developed to enhance mobility and rehabilitation through the use of various sensors. A heuristic terrain prediction algorithm, utilizing IMU sensors, helps predict and adapt to different terrains like level ground, stairs, and ramps, improving navigation for individuals with lower limb amputations [210]. Intent decoding using a CNN-based approach with IMU sensors assists in predicting user movements and intent, enhancing assistive devices' responsiveness [211]. An optical flow net combined with LSTM is used to analyze lower limb kinematics, helping to better understand and optimize movement patterns for healthy individuals and those with mobility impairments [212]. A hierarchical planner and central pattern generator enable accurate motion intention prediction and joint trajectory generation, facilitating more precise control of prosthetic devices and rehabilitation aids [213]. Finally, combining CNN and LSTM with fNIRS-BCI (EEG) in gait rehabilitation helps to refine movement patterns and improve motor control in individuals undergoing rehabilitation [214]. These algorithms contribute significantly to improving mobility, enhancing user experience, and aiding in rehabilitation.

6. AI IN IMPROVING THE QUALITY OF HEALTHCARE

6.1 How is AI Applied in Healthcare?

In modern healthcare, making good decisions depends heavily on having accurate and accessible data [215]. Doctors and healthcare workers often face difficult choices, and using smart data systems can help them make better decisions. However, when data is missing, too complex, or too large to analyze, important information can be missed. This can lead to poor decisions, delays, and higher costs [216, 217]. AI helps solve these problems by using: (a) patient data to support clinical decisions, (b) hospital data to improve operations, and (c) both patient and hospital data to help patients make informed choices. Robotic surgery is widely used across various fields, including oral and maxillofacial surgery. Other key applications include bioprinting, diagnosing diabetic retinopathy, spine imaging, and radiology [218, 219]. AI has also found a range of applications in healthcare where large volumes of structured data are available. For instance, in medical imaging, scans have been systematically collected and stored over time, making them readily available to train AI systems [220]. This allows AI to reduce the cost and time involved in analysing scans, potentially enabling more frequent imaging to better target treatment [221]. AI has already shown promising results in detecting conditions such as pneumonia, breast and skin cancers, and eye diseases [222]. In echocardiography, systems like Ultromics—trialled at John Radcliffe Hospital in Oxford—use AI to analyse heartbeat patterns and diagnose coronary heart disease [223]. Additionally, AI tools are being developed to analyse speech patterns in order to predict psychotic episodes and monitor neurological conditions such as Parkinson's disease [224]. In the field of surgery, AI-controlled robotic tools have been used in research to perform precise tasks in keyhole procedures, such as tying knots to close wounds [225]. Augmented reality also plays a role by overlaying computer-generated images onto the real-world view, helping surgeons see a clearer and more detailed view of the surgical area. AI-powered tele-surgical systems have made it possible for surgeries to be performed remotely, with senior surgeons overseeing procedures in real-time. Video imaging and communication tools offer intraoperative guidance, which is especially useful in areas with limited clinic access, travel restrictions, or during pandemics [226]. With the rise of minimally invasive techniques, AI and AR-based surgical mentorship is becoming a practical option [227]. Expert surgeons can provide real-time advice directly on the operating screen, helping guide decisions like incision points or tool selection. Additionally, computer vision and data analysis can be used to monitor and improve a surgeon's workflow. Robot-assisted surgery, being minimally invasive, has been shown to significantly reduce patients' hospital stay durations [228]. Artificial intelligence (AI) is becoming increasingly popular in mental health care, as patients seek convenience and instant feedback [229]. Since emotional and mental health is often expressed through language, therapists have traditionally relied on conversations and patient narratives for assessment. Recent AI advancements offer new possibilities by enabling systems to interpret emotional cues from a broader range of data sources [230]. The use of computational language tools and emotion detection has significantly advanced mental health research. Natural Language Processing (NLP), a technique in computer linguistics, allows machines to understand and analyze human language. Sentiment analysis, a subset of AI, helps interpret emotional meaning behind text and speech [231, 232]. By combining NLP with sentiment analysis, data scientists have developed models capable of identifying emotional states from written content [233]. These tools are now applied in healthcare to gain deeper insights into a patient's mental and emotional health. For instance, NLP models have been used to identify signs of suicidal ideation in clinical records, predict suicide risks through online content, and detect mental health disclosures on platforms like Twitter [234]. Beyond individual care, these models have been employed at a broader scale to track mental health trends across populations. One example includes mapping behavioral health issues across the U.S. by linking NLP results with public health data from the CDC. Researchers have also achieved high accuracy in identifying mothers at risk of postpartum depression based on their digital activity [223, 235].

6.2 Benefits of Employing AI in Healthcare

The integration of Artificial Intelligence (AI) into healthcare marks a major step toward more efficient, personalized, and predictive patient care. AI offers the potential to lower healthcare costs, better allocate resources, and enhance treatment outcomes. However, its widespread adoption comes with several challenges, including regulatory barriers, concerns around data privacy, and important ethical considerations. AI delivers economic value in healthcare mainly by enhancing operational efficiency. For instance, AI systems can interpret medical images with accuracy similar to that of human experts, helping reduce diagnostic errors and related costs [236]. Additionally, predictive analytics powered by AI can identify early signs of patient decline, allowing for timely interventions that help lower overall healthcare spending [237]. AI also has the potential to lower labor costs by handling routine administrative tasks like appointment scheduling and billing. This frees up healthcare professionals to concentrate on more complex clinical responsibilities [238]. As a result, productivity increases, and healthcare workers can deliver more focused and personalized care. Additionally, AI's ability to rapidly analyze large datasets helps healthcare providers use resources more efficiently. By identifying patterns in patient data, hospitals can better allocate staff, equipment, and services, reducing waste and improving patient outcomes [239]. AI technologies can greatly improve patient safety by reducing medical errors, especially in drug prescriptions and dosage decisions, where they help detect harmful interactions or side effects. They also support preventive care by analyzing patient history and lifestyle to identify risks for chronic diseases, enabling early intervention. Additionally, AI-powered diagnostic tools make quality healthcare more accessible in rural and underserved areas, cutting travel costs and ensuring timely treatment, which lowers the chances of serious conditions requiring expensive care.

6.3 Challenges in Incorporating AI in the Healthcare Sector

AI, owing to its data-driven nature is entirely dependent on receiving sufficient patient data in order to be effectively implemented in healthcare. The implementation of AI anywhere comes with its own set of concerns and drawbacks however, in the healthcare sector in particular these concerns are amplified because of the private and sensitive nature of the patient data that is fed into these systems. Medical records often contain highly personal information such as medical history, genetic data, mental health records, and treatment outcomes, all of which must be carefully protected to maintain patient confidentiality and comply with legal standards. The risk of data breaches, misuse of information, and unauthorized access becomes a major ethical and operational challenge. Furthermore, there is growing concern around algorithmic bias, where AI systems trained on non-representative datasets might produce skewed or unsafe recommendations, particularly for minority or underrepresented populations. Transparency in how these systems make

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decisions also remains a critical issue, as medical professionals must be able to trust and interpret AI-driven insights to make life-impacting decisions. Therefore, while AI offers substantial potential for enhancing diagnosis, treatment, and patient outcomes, its deployment in healthcare demands robust safeguards, accountability frameworks, and a continuous emphasis on fairness and privacy.

7. CONCLUSIONS

This review paper aimed to explore the potential, applications, and challenges of Artificial Intelligence (AI) across four critical sectors: sustainability, education, healthcare, and physical disabilities. By analyzing current literature, the study highlights how AI is reshaping these fields through smarter systems, improved decision-making, and more personalized solutions. In sustainability, AI supports climate modeling, resource optimization, and smart environmental management. In education, it enhances personalized learning and accessibility, especially for students with disabilities. In healthcare, AI improves diagnostics, surgical procedures, mental health monitoring, and hospital operations. For individuals with physical disabilities, AI-driven assistive technologies are enabling greater independence and participation in daily life.

However, this study is not without its limitations. Being a general overview, it does not dive deeply into technical implementations or sector-specific policy frameworks. Additionally, the review is limited to publicly available and recent academic and grey literature, which may not capture all cutting-edge developments or regional perspectives. Another limitation is the lack of empirical data or experimental analysis, as the paper is focused on secondary sources. Despite these constraints, several key insights emerge from the review. Firstly, while AI offers substantial benefits, concerns regarding data privacy, algorithmic bias, transparency, and equitable access remain significant. Secondly, responsible AI development requires cross-sector collaboration, robust ethical standards, and inclusive design practices to ensure that no group is left behind. Lastly, AI should be viewed not as a replacement but as a complement to human effort—supporting decision-making, expanding capabilities, and improving quality of life when implemented thoughtfully.

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