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Contemporary Challenges in IT: AI in Healthcare and Education

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ABSTRACT

The article examines the modern issues and possibilities of Artificial Intelligence (AI), both in healthcare and education, as two of the most pressing spheres of society that require AI implementation. As countries stay on track to achieve the United Nations Sustainable Development Goals, specifically SDG 3 (Good Health and Well-being) and SDG 4 (Quality Education), AI has become a disruptive tool that could change the way service delivery is done, how people access services, and the outcome. However, the paper stresses that AI could worsen the current inequalities unless close attention is paid to these issues through careful ethical governance, inclusive design, and investment in digital infrastructure.

AI applications in healthcare include various types of diagnostic imaging, telemedicine, clinical decision support systems, and new models of care delivered through technologies such as NLP and predictive analytics. The case studies of the U.S. and Rwanda also represent the opportunities and hazards of AI, such as diagnostic level accuracy, data fragmentation problem, algorithm bias, and minimal clinical validation.

In education, AI is used in the form of intelligent tutoring systems, adaptive assessments, and automation of administration and learning. Such efforts as adaptive learning provided by Arizona State University and the Rori AI tutor project in Ghana show opportunities related to equity and scalability. However, there is still some worry about privacy, algorithm discrimination, and ineffective teacher training.

Through a comparative analysis of the two sectors, the article provides an insightful look into their similarities, including infrastructure requirements and data bias, as well as the differences between user adoption, regulation, and risk tolerance. It proclaims cross-sectoral policy frameworks, capacity-building programs, and an ethics approach to AI design to guarantee sustainable and fair AI adoption.

Keywords: Artificial Intelligence, Healthcare Innovation, Educational Technology, Ethical AI Governance, Digital Equity, Predictive Analytics

I. INTRODUCTION

Incorporating Artificial Intelligence (AI) into fundamental areas of public services is not only a milestone opportunity but a multifaceted problem of the 21st Century. Two of these areas are healthcare and education because of the human reach of these sectors and the potential they hold concerning an emerging digital technology. As countries progress towards achieving the United Nations Sustainable Development Goals, particularly SDG 3 (Good Health and Well-being) and SDG 4 (Quality Education), AI is firmly established to enhance accelerated progress. Nonetheless, its effects may be disruptive when poorly managed using poor moral codes, insufficient infrastructure investment, and exclusive designs, especially in low-resource settings (United Nations, 2025).

In healthcare, the list of uses of AI has now expanded to include diagnostic imaging, clinical decision support, pandemic preparedness, and the operations of hospitals (Bajwa et al., 2021). The COVID-19 pandemic accelerated the usage of AI-enhanced telehealth platforms, demonstrating the potential of broadly facilitated access and the drawbacks of the inequitable application (Reddy et al., 2020). As Castro (2024) notes, while speaking on AI's power to transform medicine in his TED talk, "it is human. Plus, AI will beat the best human or the best AI. Together, we are an unstoppable force.”

In education, AI is replacing the pedagogy and assessment methodology with adaptive learning environments, intelligent tutoring systems, and automated feedback (Holmes et al., 2021). Such innovations present the chance of personal learning and inclusive learning. However, data security, dehumanization, and a lack of digital equality remain issues (Williamson & Eynon, 2020). Furthermore, the labour market is changing, so the students are struggling with the insecurity about their future career trajectory and how automation can affect future employability.

The article provides an inter-sectoral analysis of the impact of AI on healthcare and education. It uses international case studies, regulatory investigation, and input from practitioners to discuss how innovation might be directed to the realization of equity, effectiveness, and sustainability in both areas.

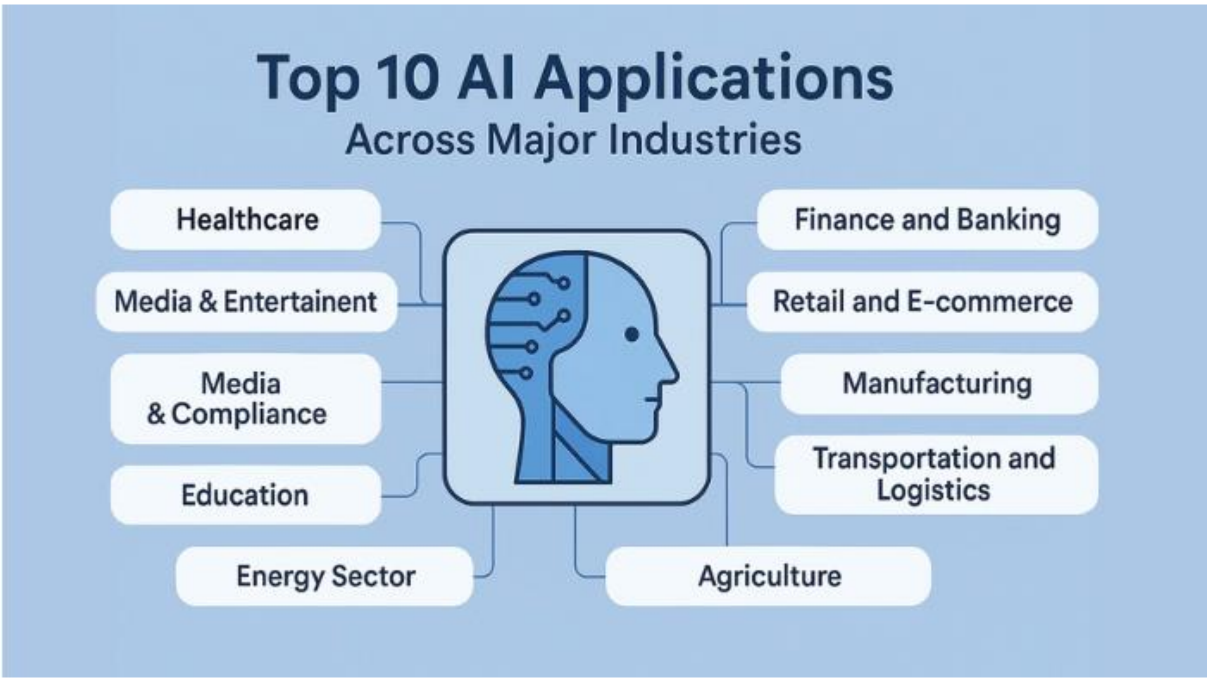

Figure 1: Top 10 AI Applications Across Major Industries
Source: Codewave (2025)

II. LITERATURE REVIEW

AI in Healthcare

Artificial Intelligence (AI) is becoming one of the key dimensions changing healthcare systems concerning the costs, access, and personalization. Varnosfaderani and Forouzanfar (2024) argue that AI has found more applications in diagnostic imaging, operational optimization, and the workforce of patients with wearable technology. In their review, they delineate clinical decision-making as one of the primary beneficiaries where AI tools have profound effects on the precision and efficiency of the diagnosis.

AI has also made it possible to manage hospitals much more efficiently and less dependent on administrative work. Nonetheless, integration issues remain, especially regarding the protection of ethical codes. Hossain et al. (2023) also note that a subset of AI known as Natural Language Processing (NLP) is being used to interpret Electronic Health Records (EHRs) and provide usable information to guide clinical decisions.

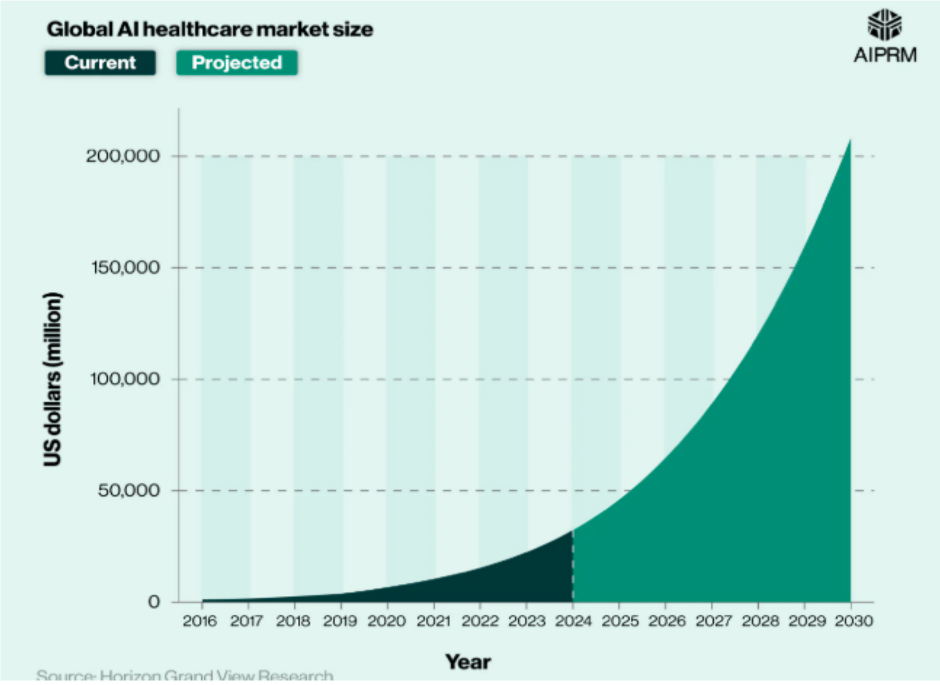

Figure 2: A breakdown of the global AI market size in healthcare current and projected
Source: AIPRM (2024)

AI in Education

Artificial Intelligence is transforming pedagogy in the education sector by producing adaptive pairing frameworks, intelligent IQ systems, and real-time response tools. Yaseen et al. (2025) discovered that this category of technologies can increase students' interest, as 72% of surveyed students reported increased interest when using AI-driven tools tailored to their levels of digital literacy. The adaptive systems can respond dynamically to the stage of learners, and interactive tools enhance deeper involvement.

According to Eynon (2023), developing AI tools for educational purposes is currently focused on the relevance of governance models and multi-stakeholders' involvement to ensure maximum benefits. These matters are especially crucial since AI systems are increasingly applied during admissions, assessments, and instructional design. Bond et al. (2024) also note that 81% of AI applications in education stem from high-income countries.

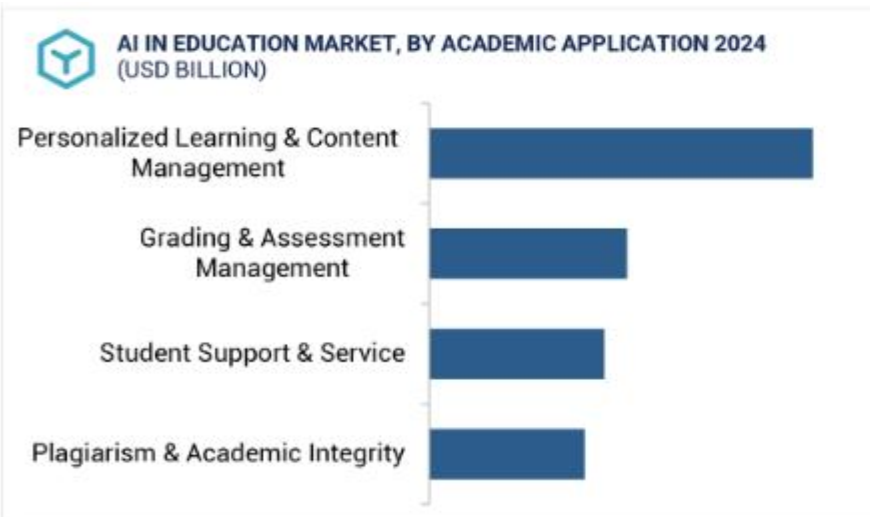

Figure 3: AI in Education Market, By Academic Application 2024 (USD Billion)
Source: Marketsandmarkets (2023)

Cross-Sectoral Reviews and Meta-Analyses

The comparisons of the cross-sectoral applications of AI shed light on common issues and area-specific opportunities. In a study on medical students in Saudi Arabia, Alkhayat et al. (2025) observed mixed feelings about AI in medical education, with 54% having a positive attitude and 31% being sceptical of AI. The research indicates broader concerns regarding the pedagogical success and long-term effects of AI on professional identity and the process of clinical judgment. In their turn, Jamal Eddine et al. (2025) discussed how ChatGPT was used in STEM, healthcare, and social sciences and noted differences in the manner of adoption and associated concerns. The biggest privacy concerns involved healthcare respondents, whereas text-heavy disciplines were more prone to academic integrity risks.

Meta-analyses also support the patterns. According to Younis et al. (2024), some significant fields in which AI transforms healthcare are diagnosis at 78% patient interaction at 65%, and administration work at 59%. Similarly, Bond et al. (2024) identified that personalization work by AI systems stood at 74% and adaptive systems at 68% as the most popular applications in AI research in higher education.

Identified Gaps and Limitations

In both industries, some vital shortcomings curtail the proper use of AI. The incompleteness of the training data concerning the range of demographic groups in healthcare can result in bias in the algorithms and inaccurate diagnosis, according to Norori et al. (2021). He concludes that 67% of AI applications in health studies he reviewed lacked diverse demographic representation, increasing the risk of misdiagnosis, especially in marginalized populations. Many AI systems lack model validation and do not consider data imbalance (Hossain et al., 2023). Such limitations of methods reduce the validity of AI tools in practice.

The desire to make technical solutions the primary step in solving the problems in education tends to blur the socio-political aspects of adopting AI. Eynon (2023) complains of tunnel vision on algorithmic fairness at the expense of further inquiring about power, justice, and stakeholders. Moreover, Bond et al. (2024) observe that studies are not diverse in context, as most are conducted in high-income countries. These gaps indicate that interdisciplinary, ethics-driven, and context-sensitive AI development is required.

Table 1: Challenges vs. Opportunities in AI Integration

Category	Challenges	Opportunities
Healthcare	• Integration issues (ethical, technical) • Lack of annotated and diverse data (67%) • Algorithmic bias in biomedical records • Privacy and data protection concerns	• Improved diagnostic imaging (78%) • Enhanced clinical decision-making (up to 70% accuracy gains in some AI tools) • Efficient hospital operations (59% cited in meta-analyses) • NLP enabling structured EHR interpretation
Education	• Algorithmic and structural biases in AI tools • Sociotechnical issues (fairness vs. power/justice) • Overreliance on technical solutions	• Adaptive learning systems tailored to student levels (68%) • Increased student engagement and digital inclusion (72%) • Real-time interactive teaching tools

	• Lack of diverse context in studies (81% from high-income countries)	• Improved assessment and instructional design
Cross-Sector	• Professional identity concerns in education (31% skeptical of AI adoption)	• Broader adoption across STEM, healthcare, and social sciences
	• Privacy and academic integrity concerns (esp. ChatGPT use)	• Growth in personalized, adaptive systems across sectors
Gaps	• Data imbalance and limited model validation	• Growing emphasis on interdisciplinary, ethics-driven, and inclusive AI development

III. CONCEPTUAL FOUNDATIONS

Background

The 21st-century digitization era revolutionised how information is generated, disseminated, and responded to in almost all spheres of activity. In the information technology (IT) sector, the transition has enabled new and unimaginable possibilities, especially with the application of Artificial Intelligence (AI). Human and mechanical decision-making roles remain blurred as organisations introduce digital platforms to some of the primary operations. Nothing is more conspicuous in this than in the healthcare and educational spheres of the public that have depended on human skill and person-to-person trust.

Machine learning (ML), natural language processing (NLP), and predictive analytics are AI technologies used in both disciplines to speed up service delivery and transform stakeholders' expectations (Bekbolatova et al., 2024; Kamalov et al., 2023). These trends require a coherent and complex interpretation of the interrelationship between digital transformation, ethical obligations, and local capabilities, especially in environments with diverse infrastructure and institutional preparedness.

Purpose and Scope

This paper endeavours to discuss the revolutionary potential of AI in two pillars of the collective services: the healthcare and the education sectors. Not only are these sectors at the core of success to the United Nations Sustainable Development Goals (SDGs) specifically SDG 3 (Good Health and Well-being) and SDG 4 (Quality Education), but also important points of contact on the measurement of equitable digital progress across nations and territories (UNDP, 2025).

One of the primary purposes of undertaking such analysis will be to compare the use and influence of AI technologies in high-income and low-resource settings. High-income countries (HICs) tend to be the most innovative and deploy AI. In contrast, low and middle-income countries (LMICs) have a structural, infrastructural, and ethical barrier to adopting similar technologies (Zuhair et al., 2024). For example, a radiology unit in Sweden could use AI provided by real-time diagnostic feedback. In contrast, a rural clinic in sub-Saharan Africa could not maintain a stable internet connection, much less could it interpret digital diagnostics. In the same way, an urban school in Singapore could invest in adaptive learning software to provide individualised lesson plans. In contrast, a public school in a developing area might lack access to electricity or even computer literacy.

This article discusses the potential impact of AI on the delivery of services, its outcomes, the creation of more accessible systems, and the risks of its use by paying special attention to sector-specific use cases and the governance dynamics. The comparative lens not only helps to spot international inequalities but also helps to point out common problems, including algorithmic prejudice, data privacy issues, and conflict between automation and human agency. Finally, fair and evidence-based AI integration is promoted in the article, which depends on local requirements, ethical values, and active governance.

Defining AI in Context

Artificial Intelligence can be defined as the process of simulating human Intelligence in computerized apparatus designed to think, learn, and adapt (Stryker & Kavlakoglu, 2024). This is represented by a variety of technologies in the field of healthcare and education, which include:

- Machine Learning (ML): Learning algorithms based on vast data collections to make predictions or decisions (Sarker, 2021). ML is used in healthcare to assist in diagnostics and give treatment recommendations, and in education, it drives adaptive learning modules.
- Natural Language Processing (NLP): The capability of machines to comprehend and produce human language (Stryker & Holdsworth, 2024). Systems based on NLP are found in clinical documentation, chatbots with patients, and automated graders.
- Expert Systems: AI rule-based systems that imitate human expertise in decision-making, especially in medical triage systems and educational test facilities (Rashid & Kausik, 2024).
- Computer Vision: The ability of computers to recognize visual images. It is applied in radiology, healthcare, and visual recognition in education (Javaid et al., 2024).

Although these technologies are potent, they are not neutral about value. Data quality, institutional priorities, and sociotechnical contexts influence their development and deployment. Incorporating AI into the various sectors responsibly requires familiarity with such nuances.

AI Lifecycle Flowchart

AI systems follow a lifecycle from conception to deployment and monitoring (GCORE, 2025). The typical stages include:

1. Planning and Data Collection
2. Model Development
3. Model Validation
4. Deployment
5. Monitoring and Maintenance

There are certain risks and liabilities associated with every stage. An example of this can be seen in the necessity of collecting data unbiasedly with consent. The training of models should be representative of the different user groups in order to prevent institutional bias. It is mandatory to receive constant feedback to recalibrate systems in a dynamic environment, such as a hospital or a classroom (GCORE, 2025).

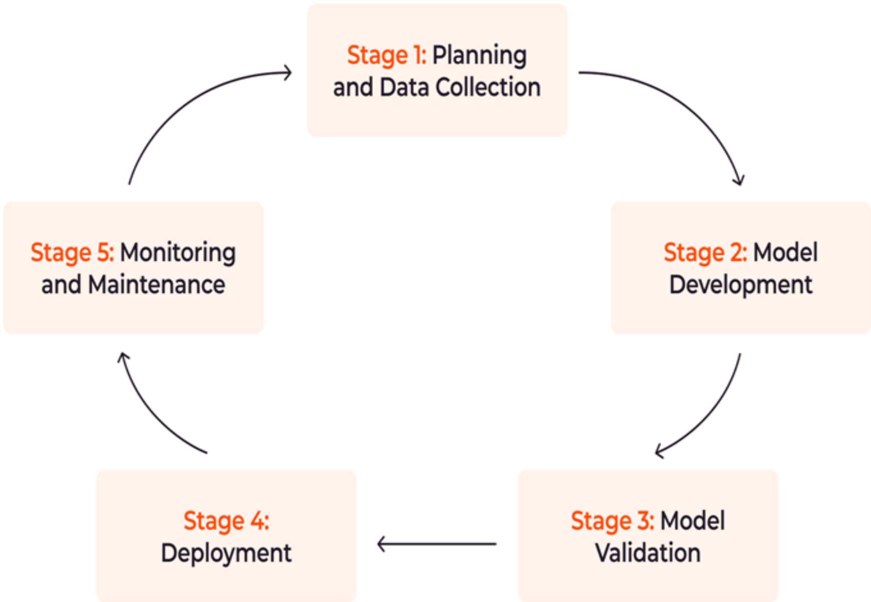

Figure 4: AI Lifecycle Flowchart
Source: See Figure 3, GCORE (2025)

Digital Maturity Gap

Although the digital maturity of healthcare and education is promisingly high, it displays different rates in various countries. Electronic health records (EHRs), telehealth platforms, and real-time clinical decision support systems are becoming commonplace healthcare systems in high-income regions that have increasingly turned digital (Zhang & Saltman, 2021). Conversely, most education systems, particularly those in LMICs, are still under-digitised, with low access to infrastructure and digital literacy education (Gottschalk & Weise, 2023). This disparity leads to skewed preparedness towards the adoption of AI tools. Furthermore, education continues, even in high-income contexts, to attract a disproportionately small amount of investment and policy promotion of AI-driven change relative to the healthcare sector. These sectoral differences require specific measures corresponding to the local situations prevailing in the technological, institutional, and cultural areas.

Ethical and Policy Frameworks

Extreme ethical issues related to AI in healthcare and education should be resolved by implementing effective control schemes. Data governance is important since health and student data are sensitive. The issues concerning data ownership, storage conditions, and sharing practices are still controversial (Williams et al., 2024). Privacy also plays an important role, mainly when personal information is gathered, analysed, and used to predict behaviour by AI systems. In both of these sectors, a breach may be life-altering (Williamson & Prybutok, 2024).

The problem is that accountability mechanisms are poorly established. Regarding clinical practices, it remains unclear who will be at fault for an AI-assisted misdiagnosis: the doctor, the developer, or the hospital (Cross et al., 2024). Automated tests may strengthen bias in education unless they are frequently exposed to auditing (Al-Zahrani, 2024). Transparency and explainability are other issues with which policy frameworks must contend- ensuring that users can challenge and understand AI systems. Worldwide institutions such as UNESCO and the WHO have started to write international guidelines, but compliance and adaptation are significant obstacles.

IV. AI IN HEALTHCARE

Current Applications

AI has grown in popularity in modern healthcare practice and has a broad spectrum of applications, including diagnosis, predictive analysis, and telemedicine. AI used in imaging and deep learning is changing pathology and radiology in diagnostics. For example, high-performance segmentation of CT-based biomarkers aids automated risk stratification, although its utilisation in the real world has been limited (Vargas-Santiago et al., 2025). Machine learning models and data in the electronic health record (EHR) traditionally have been used to predict readmission risk, model patient outcomes, and plan resources (Banga, 2024).

The use of AI tools in telehealth platforms is growing so that chronic conditions can be monitored and patient triaging can be automated. Within a remote patient monitoring (RPM) ecosystem, such metrics as blood pressure or glucose levels can be measured continuously, and predictive alerts are triggered according to the lifestyle and medical history data (Ko et al., 2023). Chatbots and virtual assistants like Cedars Sinai CS Connect automate the patient intake process and give advanced diagnostic suggestions, giving physicians more time to spend on the patient. In a new report, only 77% of AI-provided treatment recommendations were optimal compared to 67 per cent produced by human providers (Sweeney, 2025).

Challenges

Artificial Intelligence in healthcare has major obstacles despite its potential. The fragmented and decentralised phenomenon of health data is one of the key problems. Information is usually isolated in different systems or even on paper, which reduces training and prediction effectiveness, particularly in under-resourced areas (Ahmed et al., 2023). Another issue is clinical validation: most AI systems have no prospective evaluation or public comparative performance reporting, which leaves their efficacy uncertain (Vargas-Santiago et al., 2025).

Besides, there is also the ethical problem of algorithmic bias and fairness. The models trained on non-representative datasets produce biased results disproportionately unfavourable to underrepresented communities (Chen et al., 2023). Employee preparedness is also low: AI training is unorganised, and relatively few healthcare providers are prepared. Nurses complain of a lack of formal training and are unsure how to incorporate AI into clinical practice, potentially threatening its safe and effective application (Alzghaibi, 2025).

Case Studies

EHR Use in the U.S.

The healthcare network of Cedars-Sinai, a major nonprofit hospital in Los Angeles, introduced the CS Connect in 2023 to mitigate the increasing clinic and patient loads and clinician burnout due to inefficient recess management inefficiencies. CS Connect is deployed in collaboration with K Health and combines artificial Intelligence and electronic health records (EHRs) to provide 24/7 virtual care (Sweeney, 2025). Over 42,000 patients have been served in the application, which streamlines the intake procedures, triages symptoms, and offers drug suggestions.

The AI in CS Connect replicates physician reasoning by comparing patient responses with massive datasets in an Electronic Health Record, automating diagnosis of patients and enabling physicians to spend more time solving complex care challenges instead of filling paperwork and typing in the same information (Sweeney, 2025).

Cedars-Sinai supports its claims through a 2025 study, which assessed 461 cases on AI-based treatment regimens of such symptoms as respiratory and urinary infections. It was discovered that 77% of AI recommendations were rated as clinically optimal, which contrasts with 67 per cent of physician ones (Zeltzer et al., 2025). Specifically, the AI tool was more guideline-adherent, prompting it to prescribe bacterial cultures before prescribing antibiotics in cases of recurring UTIs.

Diagnostic AI in Rwanda

Rwanda has pioneered adopting AI-based healthcare technologies in sub-Saharan Africa, with programs to manage heart failure (HF). A recent study comparing six machine learning (ML) models showed that the Random Forest (RF) classifier outperformed other models in predicting hospital readmissions of HF patients dramatically, with an AUC of 94%, and this is as opposed to a 57% AUC from a previous decision trees model (Rizinde et al., 2023). The predictions allow healthcare providers to act pre-emptively, make treatment approaches person-centric, and divide resources more efficiently.

Rwanda is also rising to the level of use in diagnostic accuracy of frontline healthcare workers with the help of locally trained AI-based decision support tools. By working in conjunction with an AI-based platform known as *Digital Umuganda*, clinicians who have been locally trained in Kinyarwanda receive specialist support that improves the accuracy of diagnoses to 71% in comparison to the 8% accuracy when not using the locally trained models (World Economic Forum, 2025).

User Perspectives

Thematic analyses and interviews produce subtle opinions of clinicians and nurses. One qualitative synthesis concluded that healthcare professionals widely regard AI as reducing an administrative burden and enhancing efficiency, not replacing human judgment (Fazakarley et al., 2024). In Jordan, nurses highlighted the need for a systematic form of continuous AI education to feel comfortable using it. They raised concerns regarding data security and the possible loss of their jobs. As one optimistic participant said, "AI takes over the tedious data entry tasks so that we can focus on the patients' needs (Almagharbeh et al., 2025)."

Cost Analysis

Economic commentary on the use of AI in healthcare is still taking shape, albeit at an early stage of development. Clinical decision support systems (CDSS) applications have exhibited impressive economic value, mainly in containing expensive hospital readmissions through AI programs. A survey on a regional hospital in the city of La Crosse in Wisconsin studied the effects of a commercially sold AI tool on readmission during 2,460 hospitalisations (Romero-Brufau et al., 2020). The application evaluated the risk of readmission of any admitted patient and provided specific recommendations on interventions.

The hospital's readmission rate decreased within six months of use, from 11.4 to 8.1 per cent, a statistically significant relative decrease of 25 per cent compared to other similar hospitals used as controls ($p < 0.001$). Among the patients with high risks as confirmed by the system, only 11 needed to be treated to achieve one readmission prevention, demonstrating its cost-effectiveness and clinical significance.

The returns on AI-based investments in healthcare are high, particularly in the case of hospital readmissions. As an example, predictive artificial Intelligence (AI) can present a reduction in readmission up to 20% resulting in U.S. hospitals saving millions of dollars in preventable care costs each year. Along with the short-term savings explained above, AI can provide long-term cost savings, compared to manual screening and follow-ups, due to its scalability and candidate growth as AI learns. Nevertheless, intensive initial costs to set up, poor digital infrastructure, and lack of workforce training are obstacles to implementation faced by low- and middle-income countries (LMICs). Without tactical funding schemes and internationalist affiliations, the cost-benefit power of AI might be off-limits in resource-poor conditions.

Table 2: Case Study Matrix in Healthcare

Country	AI Use Case	Outcome	Challenges
United States	CS Connect at Cedars-Sinai: AI + EHR system for virtual care, triage, and diagnosis support	• Served 42,000+ patients • 77% of AI treatments rated clinically optimal (vs. 67% for physicians) • Reduced clinician workload and burnout.	• Integration with EHR systems • Physician trust in AI recommendations
Rwanda	Random Forest-based prediction of heart failure readmissions and *Digital Umuganda* for AI-assisted diagnosis	• HF readmission predictions reached 94% AUC • Diagnostic accuracy improved from 8% to 71% for frontline workers using AI.	• Infrastructure gaps • Training needs • Ensuring culturally and linguistically relevant AI

V. AI IN EDUCATION

Current Applications

Artificial Intelligence (AI) has been growing in the education system in most parts of the world, transforming how students are educated and how trainers teach students. Personalised learning is one of the most popular applications of AI in learning. The educational process uses AI-based platforms that study students' learning profiles, speed, and progress and adjust accordingly.

For example, some lesson delivery platforms, such as Squirrel AI in China, have been applied to provide customized lessons and yield positive results on student engagement and achievement (Mirea et al., 2025). Through the algorithms, these systems detect the gaps in knowledge and suggest specific content, changing the corresponding universality system into a highly interactive one.

Intelligent tutoring systems (ITS) are also significant applications in which one can get real-time feedback and a tutor can be simulated to act one-on-one. Examples are Carnegie Learning and ALEKS, which have proved successful in math and science. The study by Vieriu & Petrea (2025) stated that ITS enhances conceptual learning and retention, especially for those students who underperform.

Automation of the administration is also noteworthy. Student services like admissions, scheduling, and answering frequently asked questions are being streamlined using AI chatbots and virtual assistants. Schools such as Georgia State University report that AI chatbots decreased the summer melt by 21 per cent, since they help do complicated administration work with the students (POPESCU et al., 2023).

Finally, new automation grading and classroom analytics are available with AI tools to help teachers. The scope of applying Natural Language Processing (NLP) systems, such as Gradescope, would help automate the scoring of written responses to a greater extent and with greater consistency (Wilson et al., 2024).

Challenges

Besides its potential, the application of AI in learning carries several obstacles. Algorithmic bias is one of them. Because AI systems use past data to train, they can replicate societal injustices. An example is adaptive learning platforms that present the mostly Western training sets of data inappropriately by not being culturally representative of other types of learning (Williamson & Eynon, 2020). Inequitable access to AI-enhanced tools still occurs, particularly between the well-endowed and underprivileged institutions. This lack of parity in supply and access can exacerbate disparities based on geography and socioeconomic status.

Digital inequity is also a problem. The availability of AI-enhanced tools is usually contingent on the financial capacity of a school, further institutionalising imbalance in education between the urban and rural areas, or between public and private schools. The UNESCO report 2025 showed that 10% of schools and universities have successfully developed a framework to guide the integration of responsible AI (UNESCO, 2025).

There is also the fear of privacy. AI systems use student data en masse, and the approach is associated with privacy, consent, and ethical practices. There are no strong governance structures, thus there is the possibility that the sensitive data would be misused or given a chance of being exploited (Xue et al., 2025).

Finally, there are steep learning curves that teachers encounter. Professional development is also necessary to aid the effective implementation of AI and infrastructure. Educators will not make productive use of these tools when adequately trained (Cardona et al., 2023).

Case Studies

Arizona State University (ASU): Adaptive Learning Program

Due to its strategic use of adaptive courseware, Arizona State University (ASU) has become a national powerhouse of digital learning innovation. The Bill & Melinda Gates Foundation supported the ASU campus-level project. It ran under the Personalised Learning Consortium's initiative at the APLU to address an increased outcome in high-enrollment general education courses (Tesene et al., 2022).

Starting with nine ground-breaking courses and growing up to more than 65 sections by 2019, the adaptive+active learning approach integrated technology-supported personalisation with a flipped classroom paradigm, resulting in higher student engagement and performance, and retention in STEM and humanities disciplines.

Under the implementation, the results of ASU saw a massive jump in the success rates. For example, the pass rate in College Algebra increased by 28 percentage points (57 to 85), and A grades in Microeconomics courses tripled. These results empirically prove that adaptive learning platforms are valuable in enhancing academic success (Tesene et al., 2022). Microeconomics students experienced a threefold increase in A grades, and failure rates dropped. As of 2019, success rates in biology have been above 90 per cent.

However, the issues linked to the continual faculty training, courseware quality, and leadership support were discovered during the physics and history courses. The experience of ASU indicates that institutional alignment, ongoing development of faculty, and evidence-based approaches constitute the key to sustainable digital education innovation (Tesene et al., 2022).

Case Study: Rori AI Tutor in Ghana

Provision and Impact

An experiment of about 1,000 pupils in Grades 3 to 9 across 11 schools in Ghana involved Rori, a chat-based math tutor provided through WhatsApp (Henkel et al., 2024). Rori is created to be flexibly applicable to even the lowest-end mobile devices with minimal bandwidth requirements. It provides 2 30-minute weekly tutoring sessions over 8 months and is supplemented with traditional classes. Students who used Rori saw an enormous increase in growth in math scores, compared to the control group, with an effect size of approximately 0.37 ($p < 0.001$) (Henkel et al., 2024).

Scalability and Equity Strengths

Considering accessibility and scalability, Rori was designed to provide the individualised math tutoring service through an app compatible with cheaper smartphones and low-bandwidth networks that many rural and underrepresented areas often use. With a conversational interface, Rori provided curriculum-based, specific prompts and feedback. This solution also democratised the one-on-one support available only in well-resourced schools.

Motivation and engagement were indicated by high input in teacher and student feedback. A teacher who participated in the program in a rural location said, "Rori allowed the students to have someone to speak to, even though it is a bot, they could feel seen (Henkel et al., 2024)." One student also commented, "I could ask the same question many times without feeling shy (Henkel et al., 2024)," Demonstrating the scalability of AI applications in low-income countries.

User Perspectives

A mixed response can be observed in the attitude of educators and students towards AI in learning. Educators appreciate how the AI tools would individualise the learning process, relieve them of repetitive work, and identify at-risk students. Students' advantages include real-time response and interactive and flexible platforms. Nevertheless, there is still a fear of algorithmic discrimination, student information privacy, and the biases in access.

According to a 2024 survey of teachers in Ghana, 71 percent endorsed the view that the AI tutor enhanced the focus in the classroom, but 64 percent of teachers wanted additional training. The rest of the students (68%) are using AI to learn at their own pace, whereas 22% have shown frustration with the lack of steady access to the internet (Talbert, 2025).

As Khan (2023) indicates in his TED talk on how AI could save education, "and perhaps the most poetic use case is if AI, artificial intelligence, can be used to enhance HI, human intelligence, human potential and human purpose." This perspective supports the view that AI is an effective tool in education.

Cost Analysis

The initial cost of implementing AI in education is very high and will require infrastructure, software licensing, and staff education. As an example, the adaptive learning pilot of Arizona State University, which was partially Gates-funded, takes the significance of strategic partnerships to balance the costs and achieve quality results. Long-term advantages can compensate for costs.

Institutionally, student retention and engagement are reported as higher, which enhances general effectiveness. Since an AI tool such as CogBooks helps eliminate the use of textbooks and facilitates teaching, it becomes sustainable in the long term. The AI-enabled tools will have quantifiable returns on investment (ROI) compared to manual grading and static teaching methods in terms of saving time, dropout rates, and increasing exam performance scores. Nevertheless, licensing costs and infrastructural considerations can restrict the scalability in low-resource settings unless subsidised or where open source exists.

Table 3: Case Study Matrix in Education

Country	AI Use Case	Outcome	Challenges
United States (ASU)	Adaptive+Active Learning (ALEKS) system for personalised learning in STEM and humanities	• Pass rates in college algebra rose from 57% to 85% • The success rate in biology was>90% • Failure rates dropped • There was increased engagement and retention.	• Continuous faculty development • Courseware quality • Leadership and institutional alignment
Ghana	Rori AI Tutor via WhatsApp for low-bandwidth	• Effect size of 0.37 in math score improvement	• Device and network limitations

	math tutoring in Grades 3–9	• Improved student motivation and peer collaboration • Scalable and equitable access to tutoring	• Maintaining curriculum alignment • Teacher engagement

VI. COMPARATIVE ANALYSIS

Similarities

The application of AI to education and healthcare has similarities in its basis. To begin with, the two industries require strong infrastructure. Neither hospitals nor schools can support the effectiveness of the AI tool without top-notch internet connectivity, quality hardware, and compatible systems. For example, the CS Connect at Cedars-Sinai and the adaptive platform at ASU needed a backend connection with existing data systems to perform best.

Second, the essence of trust is relevant in adoption. Health practitioners are concerned about over-diagnosis by the AI, and teachers are fearful of over-trusting the algorithms. Both use cases require a combination of machine output and human judgment, and the players in both areas always urge appearances of transparency, explainability, and human control to gain trust.

Lastly, the two domains share algorithmic concerns like bias and data representation. In medical care, non-diverse patient data can give a skewed diagnosis at the model's output. Western-centric data could be useless in educating students in LMICs.

Differences

Although the themes in healthcare and education are similar, their implementation and control of AI are very different. Among the differences is data sensitivity. Patients' health records are highly personal and regulated, and they cover a variety of laws, such as HIPAA in the U.S. (AMA, 2018). Educational data, by contrast, is not as sensitive, as AI is applied chiefly to improve academic performance and engagement. Although its use is covered under privacy laws such as FERPA, it is not typically held to the same statutes and legal requirements when compared to its application in healthcare.

There are also differences in the speed of adoption. Adopting AI-powered platforms has seen education institutions (especially higher ones such as ASU) implement them quickly with the help of public-private partnerships and philanthropic funds. The use of healthcare is slower since the stakes are higher, workflows are complex, and regulations are under scrutiny. A blunder in a classroom may only allow the student to be confused, but an AI blunder in the medical industry may cost a life, creating a slowdown in such rollouts.

Also, there is stronger regulatory control in healthcare. Reputable, ethical measures must be adopted against medical AI tools regarding formal clinical validation and FDA approvals. The education sector does not have centralised regulatory authorities that lead to the incorporation of AI. This omission facilitates quick experimentation and creates ethical issues regarding using student data, anti-bias, and fair access.

Finally, differences arise when aligning stakeholders. In health care, end-users include clinicians and administrators who are usually affected, and indirectly affected patients. When it comes to education, the implementation of AI is more direct, where students, teachers, and institutions are directly affected in ways that affect outcomes and expectations.

Table 4: Comparative Matrix Summary Table

Dimension	Healthcare	Education
Privacy	High sensitivity; governed by strict laws (e.g., HIPAA)	Moderately sensitive; protected by FERPA, but less regulated
ROI (Return)	Measured in reduced readmissions, improved patient outcomes	Measured in student retention, grades, and engagement
Stakeholders	Clinicians, administrators, regulators, and indirectly patients	Students, teachers, institutions, parents
Governance	Subject to FDA, clinical validation, and professional guidelines	Minimal centralised regulation; policy varies by institution
User Experience	Indirect user engagement; tools are often clinician-facing	Direct user interaction; platforms adapt to individual learning styles

Table 5: Regulatory Analysis Table

Region	Healthcare Regulation	Education Regulation	Key AI Implications
United States	HIPAA (Health Insurance Portability and Accountability Act) • It protects patient health data, • Restricts data sharing without consent • Guides secure storage and transmission of data.	FERPA (Family Educational Rights and Privacy Act) • Grants parents/students rights over education records • Limits disclosure without consent.	• AI systems must comply with sector-specific rules. • Delays in AI deployment due to fragmented oversight. • Enforcement varies across states.
European Union	GDPR (General Data Protection Regulation): • It applies to all personal health data, requires explicit consent, data minimization, and right to erasure, and includes health-specific provisions.	GDPR also applies to management of educational data requiring institutions to guarantee transparency, consent, and data protection.	• Uniform regulation promotes interoperability across borders. • Slower innovation but stronger citizen protection. • High penalties for non-compliance.
LMICs (Low- and Middle-Income Countries)	It varies widely with some countries having fundamental health data laws, and others lacking enforcement or electronic records policies.	Often fragmented or underdeveloped, education data may fall under general ICT or child protection laws, if any ara available.	• Regulatory vacuum enables faster AI experimentation but increases risks. • Weak oversight exposes users to misuse. • Donor-led AI initiatives may bypass local governance.

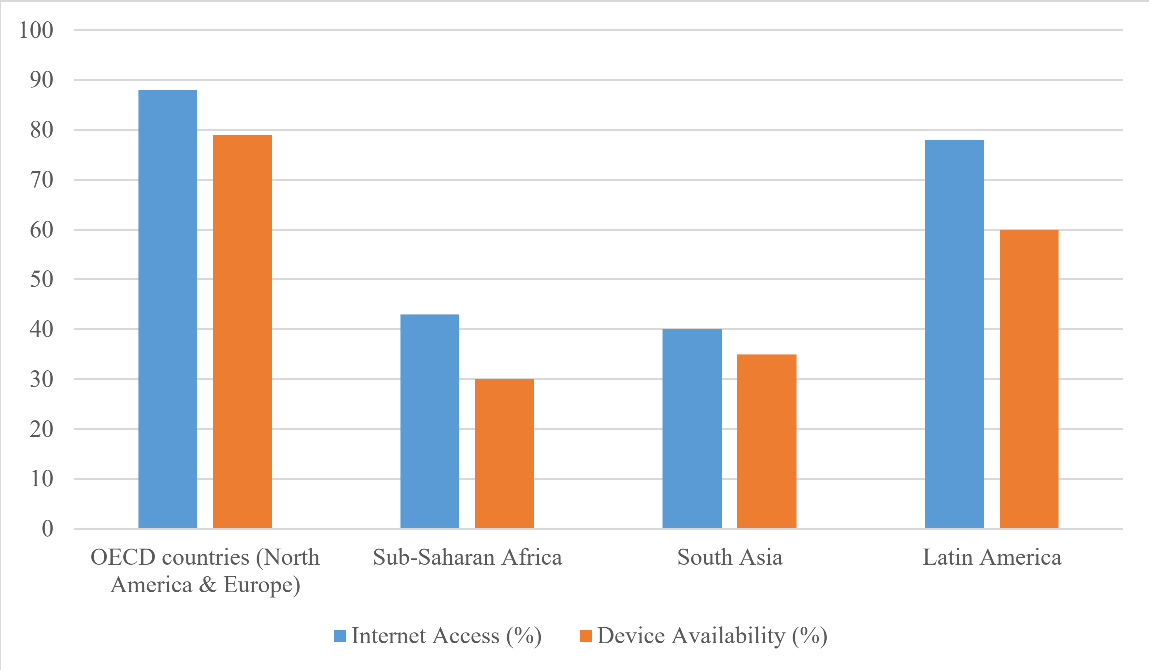

Figure 5: Bar Chart on Infrastructure Disparity

Source: CAF (2024); OECD (2023); UNESCO (2025)

Table 6: Cost-Benefit Comparison Chart for AI Adoption in Healthcare and Education

Sector	Typical Initial Cost	ROI / Benefit Metrics	Benefit–Cost Ratio
Healthcare	• AI system deployment: \$200,000 (development and infrastructure) • Annual maintenance/support: \$20,000 (Khanna et al., 2022)	• Readmission rate reduction: 25% relative (from 11.4% to 8.1%) • Operational cost cuts: 25% via staffing/resource optimization • Medicare penalty avoidance and efficiency gains: \$800K/year saved per facility (Stuti Dhruv, 2025)	• Net benefit estimated at \$100,000 vs. \$200,000 cost ratio = 1.5 (Aluru & Ethan, 2024)
Education	• Adaptive systems: \$5,000–15,000 initial licensing • Staff training: \$1,000–3,000 per cohort• Annual renewal/support: 10% of initial cost (Schiaffino, 2025)	• Student retention increase: 20–35% • Administrative savings: 40% reduction in manual workload via automation • Staff productivity gains: 50% time saved in grading large-scale assignments (UC Berkeley case) \$200K/year saved (Khanna et al., 2022; Schiaffino, 2025)	• Education ROI improvement estimated at 10–15%, rising to break-even or positive by year 3–5, depending on scale (Schiaffino, 2025)

VII. POLICY AND PRACTICAL RECOMMENDATIONS

Cross-Sectoral Governance & Ethics

In order to put responsible AI into healthcare and education, strong cross-sectoral governance systems must be available. There should be independent AI audit systems to observe the transparency of algorithms, bias, and effects. The models should be tested in terms of fairness and their effectiveness, especially when applied in vulnerable populations (Murikah et al., 2024). Also, it is imperative to establish ethics boards at the national and institutional levels. Such multidisciplinary panels, which include ethicists, technologists, clinicians, educators, and community representatives, can oversee the use of the AI tools, including whether they abide by principles of equity and data protection (Diaz Rodriguez et al., 2023). Governments should also develop binding AI codes of conduct that are enforceable across industries (OECD, 2020).

Capacity Building

AI will never be successfully implemented until frontline workers are provided with the power to engage confidently and competently. Formal AI literacy training for clinicians and teachers should be available through capacity-building programs, which should consider both technical skills and ethical issues. Health workers require instructions on interpreting the AI-generated insights in clinical practice, and the educators should learn to implement AI tools into the pedagogical planning but not to sacrifice the student-centred orientation (Altinay et al., 2024; Gordon et al., 2024). Upskilling can be done with the assistance of national training centres, online certification courses, and collaborations with higher education institutions and ed-tech companies. Governments should also invest in the train-the-trainer format to expand the capacity efficiently and sustainably, especially in under-resourced regions (Kim & Wargo, 2025).

Infrastructure Equity

The governments and international institutions need to focus on the lack of digital infrastructure that continues to occur in rural and low and middle-income nations (LMICs) to eliminate the risk of further exacerbating inequality (Wang et al., 2025). It requires strategic investments in the internet connection, power, and simple hardware in schools and clinics. The rollout of public-private partnerships can subsidise infrastructure costs, and policy incentives can attract technology vendors to subsidise affordable AI products to underserved regions (Sharma, 2024). Needs analysis should be one of the priorities of governments to highlight the so-called blind areas in infrastructure improvement. AI systems can only be deployed when the conditions are created (Transform Health, 2022). The foundation of a responsible and inclusive deployment of AI and its effectiveness is its equity of access.

Global Collaboration & Knowledge Transfer

Global bodies like the World Bank, UNESCO, and WHO should actively ensure equal access to AI and knowledge transfer between the North and South. It would be beneficial to harmonise the standards of ethical guidance and technical regulations through coordinated international programs, which may guarantee interoperability and joint responsibility (Zamiri & Esmaeili, 2024). South-South and North-South partnerships may also reinforce capacity building through mentorships, collaborative research, and regional hubs of AI policies. For example, the UNESCO (2023) initiative, AI and the Futures of Learning, enhances rights-based and inclusive adoption of AI in schools in various regions.

Table 7: Recommendation Table

Stakeholder Group	Priority Area	Action Points	Expected Outcomes	User Reflections
Policymakers	Cross-sector AI Governance	• Develop binding national AI codes of conduct for education and healthcare • Establish independent AI ethics and audit boards • Align AI deployment with GDPR/HIPAA/FERPA standards	Transparent, ethical, and inclusive AI deployment across sectors	*"AI models must be explainable. We want to know how decisions are made, especially in life-or-death situations."* — Clinician, Rwanda.
	Infrastructure Equity	• Prioritize digital infrastructure funding in LMICs and rural areas • Provide tax incentives for public-private AI partnerships • Conduct national needs assessments	Reduced digital divide and increased equitable AI access	*"AI helped us, but students in rural areas could not even log in. Equity must come first."* — Teacher, Ghana.
	Global Collaboration	• Participate in harmonizing global AI regulatory frameworks • Promote South-South and North-South AI knowledge exchanges • Support UNESCO/WHO-led initiatives	Shared AI expertise, reduced duplication, scalable innovation	*"Our diagnosis tool improved thanks to shared algorithms trained in similar African contexts."* — Public Health Official, Rwanda
Educators	Capacity Building & Training	• Integrate AI pedagogy in teacher training and certification • Partner with ed-tech providers to develop localized training- Use "train-the-trainer" models	Increased AI readiness and confidence among educators	*"I knew AI could help, but I was not trained in how to use it. We need more than just tools—we need training."* — Educator, Jordan.
	Ethical AI Use in Classrooms	• Vet platforms for bias, privacy compliance, and accessibility • Ensure data transparency and obtain student consent where applicable	Ethical learning environments; increased trust in AI tools	*"AI shows promise, but I worry about how my child's data is being used."* — Parent, Arizona
	Adaptive Learning Implementation	• Use AI for personalized learning and early risk detection • Advocate for open-source or subsidized	Improved learning outcomes; minimized	*"AI helped me ask questions without feeling shy. It felt like someone saw*

		adaptive platforms in low-resource schools	dropout and disengagement	*me."* — Student using Rori, Ghana
Health Leaders	Workforce Preparedness	• Include AI competency in continuous professional development for clinicians. • Provide practical training on interpreting AI-generated insights	Safe and effective use of AI in clinical practice	*"We don't fear AI, we fear not understanding it."* — Nurse, Jordan
	Bias and Validation	• Demand external clinical validation and public performance reporting • Use representative datasets in training AI models	Reduced algorithmic bias; enhanced diagnostic equity	*"If AI is trained on Western patients, it might miss what's common here."* — Frontline health worker, Sub-Saharan Africa
	AI-Enhanced Clinical Tools	• Adopt AI decision-support tools where proven cost-effective (e.g., reducing readmissions) • Ensure tools are integrated with EHRs and subject to regular audits	Better patient outcomes, cost savings, and optimized workflows	*"With CS Connect, I finally spend more time with patients instead of typing endlessly."* — Physician, Cedars-Sinai

VIII. DISCUSSION

The comparative discussion of AI in the health and education sectors demonstrates common opportunities and sectoral limitations determining its output to the UN Sustainable Development Goals (SDGs), especially the SDG 3 (Good Health and Well-being), SDG 4 (Quality Education), SDG 9 (Industry, Innovation and Infrastructure), and SDG 10 (Reduced Inequalities). AI can leverage both sectors to improve the accuracy of diagnosis, personalise the learning process, and streamline administrative work. AI applications in healthcare, such as analytical, predictive, and natural language processing, enhance patient outcomes and decrease encumbrance to clinicians. In learning, adaptive systems and AI tutors also enhance student interaction and acquisition. Nevertheless, regulatory sophistication, labour preparedness, and infrastructural imbalances greatly define the state of integration and success.

The contribution of AI to SDGs is both transformative and uneven. In developed economies, there is positivity towards AI-driven platforms, which proves progress towards SDGs 3 and 4 with better education retention and fewer healthcare readmissions. In low- and middle-income countries (LMICs), as examples, AI-based diagnostic tools (such as the AI tool in Rwanda) or AI-based tutoring platforms (such as the Rori AI to tutor Ghanaian children) represent the potential to implement context-dependent AI to promote equality and innovation (SDG 9 and 10).

For example, a health worker in AI diagnostics in Rwanda commented, "I can now check more patients in shorter intervals, and identify complications sooner," reaffirming the role of AI in increasing access and timeliness of care (Rizinde et al., 2023). In Ghana, a school facilitator noted, "Rori allows the too shy or slow kids to have a voice in the classroom they otherwise did not have, and that is everything (Talbert, 2025)." AI tutoring tools can provide some level of equity to disadvantaged students.

Moreover, users' input, especially members of any marginalised groups, is not sufficiently considered when designing and assessing AI. Such exclusions thwart inclusive innovation and emphasise the importance of participatory manufacturing and interdisciplinary research. The ethical use of AI and its sustainability should be more long-term and supported by stronger policies. Clinical validation and regulation in medical practice are slow and inefficient, whereas education has no singular governance strategy. Problems with privacy, accountability, and levels of transparency of algorithms are still rather significant from the point of view of ethics. Going forward, AI systems should integrate explainability, be subjected to consistent auditing, and be co-designed with end-users to prevent misuse/ mistrust.

IX. CONCLUSION

This paper has discussed the opportunities and threats created by the use of AI in healthcare and education, and quite clearly, these can lead to faster achievement of the SDGs and but may exacerbate inequalities if deployed in a exclusive or unchecked manner. Significant highlights exist on common challenges, including data bias, infrastructure gaps, governance weaknesses, and successful applications across various global settings. Innovation has to go hand in hand with accountability to see that AI creates equity. This needs ethical frameworks, stakeholder inclusion, and context-friendly deployment strategies.

Through interdisciplinary cooperation and sustainable development, AI can become the driver of more profitable, efficient, and inclusive public service systems globally. Nevertheless, practical shortcomings exist in remarkably incomplete field-based studies in low- and middle-income countries (LMICs), where most of the AI implementations are in test stages. Future studies should focus on longitudinal and participatory research identifying real-life effectiveness, inclusivity, and sustainability of AI in public services in widely different socio-economic contexts.

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