IJEAST

INTERNATIONAL JOURNAL
OF ENGINEERING APPLIED SCIENCE
AND TECHNOLOGY

VOLUME : 10 ISSUE : 08 Print / Issue Publication Date: 12-Feb-2026

ISSN : 2455-2143

DOI : 10.33564/IJEAST.2025.v10i08.006

Indexed In

WWW.IJEAST.COM

editor@ijeast.com

International Journal of Engineering Applied Sciences and Technology, 2025
Vol. 10, Issue 08, ISSN No. 2455-2143, Pages 48-58
Published Online December 2025 in IJEAST (http://www.ijeast.com)

LEVERAGING ARTIFICIAL INTELLIGENCE TO EXPAND ACCESS TO QUALITY EDUCATION: ENHANCING LEARNING OUTCOMES FOR AT-RISK STUDENTS IN LOW-INCOME COMMUNITIES THROUGH PERSONALIZED AI TOOLS

Sankarshana Madhavarao

Abstract - **The research paper investigates how artificial intelligence (AI) technologies can be used to increase the number of at-risk students in low-income communities worldwide who have access to quality education. It illuminates the global educational equity crisis and the institutional constraints that disproportionately affect disadvantaged learners. The study summarises theoretical literature, experimental works, and the current AI practice, such as personalised tutoring, automated evaluation, and predictive analytics. The approach used in the article is methodological, as the author relies on peer-reviewed evidence, global education reports, and emerging cases from low-resource settings. The results have shown that adaptive artificial intelligence tools can enhance learning outcomes, promote initial awareness of declining engagement, and reduce teaching disparities in settings with a shortage of human and material resources. However, current constraints related to infrastructure, ethical issues, and contextual adjustment should be addressed with provisional fairness. The paper ends with recommendations to governments and institutions to act in policy, as well as research priorities that are driven in the future to be sustainable, culturally sensitive, and ethics-focused AI integration.**

Keywords -**Adaptive learning systems, digital divide, educational equity, intelligent tutoring systems, learning analytics**

I. INTRODUCTION

The provision of quality education remains highly unequal worldwide. The current statistics show that about 251 million children and youth are out of school worldwide, despite decades of efforts [1]. In poor nations, this inequality is particularly abhorrent, and regularly, students will either attend schools that are inadequately funded or will not attend at all, and, thus, poverty and social alienation remain cycles. The disparities are not only related to access but also to the quality of learning: as presented in Figure 1 and 2in many low- and lower-middle-income settings, a significant percentage of children who have already turned 10 years old have yet to be able to read a simple text [2, 3]. Extreme poverty still impacts 10% of people, despite efforts to reduce it, particularly in Asia. Children are more vulnerable, particularly in sub-Saharan Africa, where 49% of children live in extreme poverty, making up 52% of all extremely poor children worldwide (Figure 1). In certain regions of the world, inequality is increasing. It frequently stays unacceptably high both within and within nations, even in cases where it is declining. Since 2000, the lowest 50% of people in Asia and North America have seen a decline in their income share. It has remained far below the share in Europe, the region with the highest level of equality, elsewhere (Figure 2).

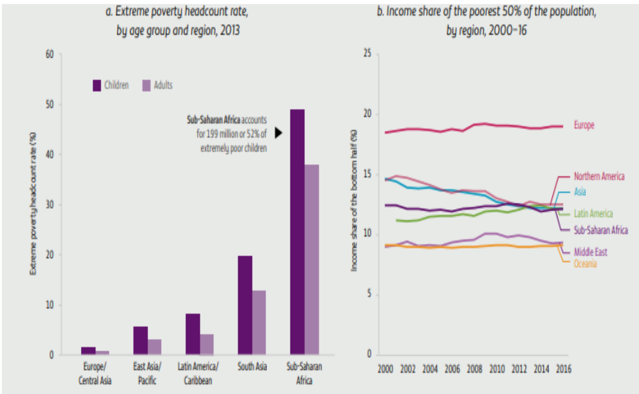

Fig. 1 Extreme poverty headcount rate, by age group and region, 2013 [4]

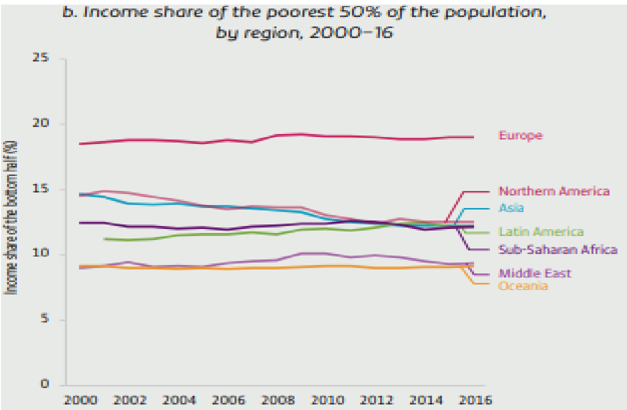

Fig. 2 Income share of the poorest 50% of the population, by region, 2000–16 [4]

The term at-risk students is thus used to describe those learners who, due to socioeconomic disadvantage, geographic distance, limited resources, or systemic marginalization (refugee, children with disabilities, language minorities, etc.), face disproportionate barriers to educational achievement. These issues usually involve a shortage of teachers, poor facilities, insufficient study resources, a disproportionate number of students per teacher, and limited access to remedial or gifted classes or to the level of study [4, 6]. The digital divide exacerbates these inequities: low-income student families often lack access to reliable devices, the internet, or digital literacy [7, 8]. These types of inequality continue to exacerbate a global educational equity crisis by undermining the notion that quality education is a universal human right. The price of stagnation is not only for those who will not advance in life, but also for societies and economies that will miss out on the potential of human resources [2]. Simultaneously with this, the recent creation and the fast evolution of artificial intelligence (AI) technologies provide a potentially revolutionary perspective of alleviating some of these inequalities. The last 10 years have seen AI-based educational innovations evolve beyond experimental research laboratories into real-world settings. Intelligent AIs can precisely and adaptively deliver instructions to the needs, speed, and contexts of individual learners through adaptive learning systems, intelligent tutoring systems (ITS), real-time feedback tools, and learning analytics [9, 11].

In contrast to the traditional one-size-fits-all approach to education, AI-based personalized learning can adjust its level of difficulty, provide remedial assistance, and offer formative feedback, thus allowing at-risk students in low-income or under-resourced schools access to high-quality educational offerings. Most recent systematic reviews of adaptive technology in education have asserted that AI-based adaptive technology increases engagement and motivation, but in most studies, meaningful knowledge retention, problem-solving, and academic improvement can be observed [7, 8, 12]. Further, AI can also be used as a low-cost, high-scaling supplement (or even a partial replacement) to insufficient teacher resources, especially in situations where shortages or high turnover of teaching staff prevent the continuity of instruction [11, 13]. It is against this context that the current article aims to analyze whether and to what extent AI can be used to increase access to quality education among at-risk students in low-income communities globally. The research question used is as follows: Can AI-driven personalized learning systems alleviate educational inequalities by enhancing educational outcomes among students in low-income and under-resourced settings? Secondary questions that can be asked are: In what ways have AI applications been promising? What are the infrastructural, pedagogical, and ethical barriers that discourage ubiquity? Under what circumstances could AI interventions be sustainable and even fairly enforced?

This research will combine empirical research synthesis and theoretical frameworks with the broader educational world to offer a critical yet balanced analysis of the potential and challenges that could constrain AI's potential for educational equity. The article is structured as follows: its initial section reviewed the challenges in education in low-income communities, the second part described the current use of AI in the field of education, and the third one supported the idea of the possibility of the advantages of AI in both at-risk and normal students, a fourth section mentioned how AI can be implemented, limitations and risks, and a final section is a policy and practice recommendations to steer effective and equitable integration of AI in the global education systems.

II. LITERATURE REVIEW

2.1 Educational Challenges in Lo-Income Communities

Low-income populations across every economic region of the world continue to grapple with deeply rooted barriers to educational equity. The shortage of qualified teachers is among the most persistent problems, alongside high teacher turnover. Modern world surveillance accounts reveal that various countries, specifically Sub-Saharan African and similar low-income countries, face significant difficulties in meeting at least minimum standards for teacher qualifications, thereby creating a massive gap between the demand and supply of qualified teachers [14, 15]. These shortages are compounded in rural or remote areas by absenteeism and the inability to retain professionals with the required qualifications due to poor working conditions and limited resources [14, 16]. In addition to human-resource limitations, students in low-income neighborhoods often lack access to higher-level coursework and other necessary learning resources. In most schools, the infrastructure is minimal, the textbooks are few, the curricula are outdated, and there are no laboratories or bit-tech facilities, all of which limit students' exposure to high-quality academic material [16, 17]. Socioeconomic factors often compound these material shortcomings; poverty can force children to work instead of attending school regularly, or lead to poor household conditions due to parents' illiteracy, the inaccessibility of reading materials, poor family stability, etc.

The most significant is the digital divide, a structural disparity that puts low-income background students at a disadvantage in an increasingly digital educational environment. In some areas, despite the availability of digital learning technologies, deriving any benefit is not an option, as too many students lack reliable internet connectivity, digital devices, or a steady power supply [18, 19, 20]. To give a few examples, high equipment and information costs, poor home connectivity, and low digital literacy among both learners and educators are significant impediments to the implementation of technology-based learning in under-resourced schools. Altogether, the lack of teachers, insufficient materials, poverty, and the absence of the digital dimension are intertwined issues of insufficient educational resources in lower-income communities, with no opportunity to enhance learning for disadvantaged students.

2.2 Theoretical Framework

The complex inequities that have developed in these areas require more than technological innovation and solid pedagogical and equity-based models. One of them is based on the theory of personalized learning, which focuses on customizing instruction to individual learners' needs, pace, and learning styles [21]. In this theory, educative interventions meet the needs of learners; therefore, they adapt to a student's knowledge level and current performance, with the intention of maximizing learning effectiveness by addressing students where they are. In addition to personalized learning, there is the sociocultural perspective, which was initially developed by Lev Vygotsky, particularly through his concept of the Zone of Proximal Development (ZPD). The ZPD assumes that learning is optimized when instruction is scaffolded: learners receive help only beyond their capabilities, thereby straining their abilities through social or mediated assistance [22]. The judicious use of artificial-intelligence-based tools can serve as digital scaffolds, suggesting hints, feedback, and step-by-step instructions that approximate the supportive role played by a past expert human tutor.

Universal Design of Learning (UDL) is another applicable framework. UDL promotes the creation of learning experiences that are open, adaptable, and responsive to the needs of diverse learners, regardless of their language, cognitive style, disability, or socioeconomic factors [23]. AI-based educational technologies, which allow personalising the content delivery, pacing, modality (ex, text, audio, interactive), and assessment, can be used to operationalise the UDL principles at scale and provide access to more learners who the traditional one-size-fits-all model of schooling underserves.

Lastly, critical pedagogy and equity-based models provide a normative perspective for assessing technology integration. In this view, technological interventions should not only reproduce the drawbacks that exist in the present on a different surface but also work against structural barriers so that marginalized learners can ensure they take up agency, make culture central, and deliver social justice. From that perspective, AI in education must not merely improve efficiency but also be used to bring about transformative equity. All of these frameworks, namely personalized learning, ZPD developed by Vygotsky, UDL, and critical pedagogy, are components of a sound theoretical framework for considering the possible contribution of AI to enhance the educational accessibility and quality for at-risk students in low-income environments.

2.3 Current State of AI in Education

Over the past few years, the use of artificial intelligence (AI) in education has grown significantly, in the form of intelligent tutoring systems (ITS), adaptive learning systems, natural language processing (NLP) systems to support literacy acquisition, programming languages, and assessment and feedback systems. An artificial intelligence-based ITS (AI) systematic analysis (2023) concluded that artificial intelligence systems may have a tremendous impact on sustainability in education, offering personalized learning experiences, data-driven decision-making, and adaptive support for each learner [24, 25]. ITS, specifically, has proved to be promising. They use AI algorithms (e.g., weak model knowledge tracking, machine learning, or large language models) to simulate students' knowledge, anticipate students' learning paths, and provide instant feedback, in some cases emulating a one-on-one tutor [12, 26].

Adaptive learning systems extend the same set of principles. Still, they often employ adaptive curriculum sequencing, which dynamically adjusts content in terms of difficulty and speed in response to performance. More recent experiments in STEM areas (e.g., mathematics, physics, programming) have shown that these types of systems can be used to increase mastery rates and enhance learning perceptions in situations where conventional teaching has proven insufficient [27, 28]. Additionally, the combination of NLP and AI-based helpers presents a new opportunity in literacy, language acquisition, and understanding. AI-powered assistants are helping institutions of higher learning answer students' questions, assist with creating quizzes and flashcards, and recommend individualized learning journeys [29, 30]. Such advances are becoming more relevant in underserved or low-resource contexts, where qualified teachers, or at least access to special education, can be limited. Artificial intelligence-based assessment tools that assign formative and summative assessment tasks to robots are also part of the broader landscape and enable more frequent, more constructive assessments and feedback without overwhelming instructors [31]. Overall, the current AI landscape in education is indicative of the data-rich, growing array of devices and applications. Although numerous applications have been developed in high-income, digitally connected settings, the conceptual and technical foundations in the literature can be applied to low-income and under-resourced settings.

2.4 Evidence of Effectiveness

The empirical studies of AI-enabled educational interventions give a moderately positive image. A recent systematic assessment of the use of intelligent tutoring systems (ITSs) in the K-12 educational context, which involved 28 studies (4,597 students), found that ITS use did not consistently yield superior performance or learning outcomes, although overall they were positively related. This means that the advantages are dependent on contextual considerations, the faithfulness of the implementation, and the excellence of the design [26]. Adaptive intelligent tutoring systems in STEM education have made substantive improvements. According to empirical evidence, including studies conducted in the context of programming and mathematics, experimental cohorts that use adaptive systems achieve significantly higher levels of mastery than control cohorts that rely on traditional teaching [27]. These results imply that planned, sequential disciplines, specifically those that can be represented using incremental problem-solving models, may be especially amenable to AI-based adaptive learning.

At the university level, AI-assisted learning tools, such as virtual teaching devices, automated content delivery models, and personalized messages, in some cases matched or even exceeded the effectiveness of traditional in-person tutoring. An analysis of recent AI applications in higher education indicated that most of the reviewed articles (21 out of 21) reported knowledge gains equivalent to or higher than those with modern approaches. However, the variation in results is related to student motivation and engagement [30, 31]. Moreover, the ability of AI to support inclusive education by enhancing adaptable content and delivery to the needs of diverse learners, including those with disabilities, language minorities, or those facing differentiated pacing, has been emphasized in modern scholarship [28]. However, there are still some significant gaps. The available evidence base is dominated by studies conducted in well-resourced, digitally connected settings (e.g., North America, Europe, East Asia), and there are few rigorous studies conducted in low-income or under resourced settings [32, 33]. Moreover, some research also cautions that poorly constructed AI devices can encourage passive learning or create a phenomenon known as cognitive offloading, where students leave the analysis to the machine rather than think critically [7, 25]. Besides, pilot results are hindered by easy ethical, infrastructural, and equity-related limitations (varying access to devices or internet services, lack of digital literacy, teacher provocation, poor policy frameworks, etc.) [7, 18].

III. AI TOOLS AND APPLICATIONS FOR AT-RISK STUDENTS

3.1. Personalized Learning Pathways

The area with the most widespread applications of artificial intelligence (AI) in the educational domain is the creation of individualized learning paths that adapt content and instructional approaches to learners' profiles. Adaptive curriculum sequencing refers to AI systems' ability to analyze trends in learners' performance, detect areas of weakness in their knowledge, and schedule learning activities to ensure they gain as many skills as possible. These systems utilize learning analytics and learner-knowledge computational models to customize content, pacing, and workload, providing a student with a personalized route through the content rather than a generic syllabus. An emerging body of empirical research indicates that this kind of individualized sequencing may lead to greater mastery and long-term commitment (compared with traditional models of teaching) (see, e.g., [27]).There is also real-time difficulty adjustment, which is another salient feature of personalized learning tools. Instructional engines powered by AI can self-adjust the complexity of tasks on an instant-to-instant basis based on the learner's progress, providing scaffolding when the current understanding is lost or increasing the level of difficulty when the learner has shown meticulousness. Notably, this dynamic adjustment aims to work within each learner's optimal challenge zone, and thus there are minimal cases of frustration and boredom. Examples mediated by AI algorithms with an abundance of readjustment to interaction patterns are platforms like Carnegie Learning in the field of mathematics or the adaptive reading helper that uses natural language processing [24].

Successful implementation is beginning to be studied as a case in both research and industry. Some of these adaptive tools can provide mathematics instruction to remote students through their mobile devices and offer personalized sets of problems aligned with curriculum standards, even in teacher-sparse settings. In low-resource settings, even pilot programmes, such as those focusing on rural populations in lower-middle-income countries, have indicated that access to adaptive instruction could help learners who might otherwise not receive the benefit of tailored support in fully occupied or inadequately resourced classrooms (see reference [13]). Though the overall evidence of large-scale directions in low-income countries is in comparatively weak condition, the response in terms of conceptual and technological foundations is becoming increasingly prepared.

3.2 Intelligent Tutoring and Support

Intelligent tutoring systems (ITS) are another development

International Journal of Engineering Applied Sciences and Technology, 2025
Vol. 10, Issue 08, ISSN No. 2455-2143, Pages 48-58
Published Online December 2025 in IJEAST (http://www.ijeast.com)

in individualized learning, and the goal is not just to sequence content but also to schedule the main aspects of one-to-one tutoring. ITS uses machine-learning models to diagnose students' misconceptions, predict likely mistakes, and provide focused, contextually relevant feedback. One of the distinguishing characteristics of such systems is that they can be used continuously, addressing the resource limitations in communities where teacher support is scarce and intermittent, or non-existent. Under conditions of a pronounced teacher shortage, AI tutors can address the most significant gaps in instruction, which might help ensure continuity of learning even after classes and reduce the effects of absenteeism or substandard teaching (cf. reference [24]).

Another important skill concerns multilingual support. The natural language processing-based tutoring agents should be able to convert instructional materials and maintain multilingual conversations, which may be beneficial to learners in linguistically diverse environments or those in which the mother tongue is not the language of learning. In situations where learning materials are seldom available in minority languages and where bilingual teaching staff is scarce, multilingual AI tools may play a monumental role in enhancing linguistic access [29]. Besides, intelligent tutoring systems feature immediate feedback mechanisms. Studies have shown that immediate feedback can improve knowledge capacity and help the learner make the process of mistake correction productive, so that the chances of developing misconceptions are low. ITS settings that offer hints, stepwise descriptions of solutions, or prominent explanatory support simulate pedagogical techniques used by trained human tutors, though in a more constrained algorithmic fashion. Although these systems cannot provide the same support as humans, there are indications of quantifiable gains in conceptual mastery and engagement, especially in STEM learning contexts (where procedural reasoning prevails) [26].

3.3 Assessment and Progress Monitoring

Also, AI technologies have demonstrated considerable autonomy in formative assessment. Algorithms to score short-answer answers automatically, provide immediate feedback on writing tasks, and analyze problem-solving processes enable frequent evaluation of learners, allowing teachers to take on untenable loads. These automated appraisals further enable learners to benefit from improved feedback processes, as well as incremental development and metacognitive reflection, both of which are essential for learners with difficulties in the learning process who need constant instruction rather than occasional evaluation.

Early detection of learning problems is another important task for AI-based assessment systems. The analytics tools can identify performance aberrations and risk signatures, such as consistent errors, slow growth, or boredom patterns, and therefore predict emergent challenges before they become as hardwired as a bout of academic failure. For high-risk students in poor areas (who, in many cases, are not provided remedial services), this ability might serve as a remedy for past disparities in early intervention resources [31]. Moreover, the intervention policies supported by learning analytics are data-driven, enabling educators and educational leaders to make connected pedagogical choices. Improved instructional differentiation, limited-resource priorities, and learner-focused profiles can help educators guide their instruction, apportion limited resources, and customize remedial programs with data rather than anecdote. Even though the question of data privacy and ethical concerns is controversial, the opportunities of analytics-assisted performance monitoring and informed responses are generally consistent with the scope of existing research into educational technologies [28].

3.4 Teacher Augmentation (Not Replacement)

Despite the constant fear of automation and job replacement, most educational studies conclude that AI could enhance existing methods rather than replace teachers. Automation of administrative tasks, e.g., scoring, attendance control, or creating individualized learning reports, could reduce teachers' workloads and enable more productive pedagogical interactions. Such automation can increase instructional time and teacher welfare, as well as decrease administrative workload, in low-income settings with large classes and heavy administrative workloads, and occupational positions are not necessarily displaced [31]. Another area that AI could help with, in reference to teaching, involves generating insights for targeted instruction. Predictive analytics can detect students who need assistance and in which areas they need it, and help instructors plan the most personalized interventions that would otherwise be unrealistic in crowded classrooms. In any scenario where professional growth/pedagogical resources are insufficient, this type of analytic support can serve to scaffold the teacher(s) themselves [26].

Another form of professional development support was also prominent during the emergence of AI usage. AI-based platforms can enable educators to access instructional resources, data-supported lesson plans, peer networks for collaboration, and micro-training. In remote or underserved regions, such support offers a chance to continually grow professionally, which may reduce isolation and turnover resulting from poor training and a lack of technical support [24].

3.5 Engagement and Motivation Enhancement

In addition to instructional customization, artificial intelligence (AI) applications are increasingly equipped with mechanisms to increase engagement and motivation among learners. Gamification, in the form of badges, progressive systems, point systems, narratives, and interactive challenges, is designed to increase feelings of persistence and enjoyment among learners. Empirical evidence indicates that carefully designed gamified learning environments can promote intrinsic motivation and increase persistence in learning among otherwise disengaged students in a conventional classroom. For at-risk learners who are adversely affected by educational conditions or who inherently lack motivation, gamification can cause quantifiable motivational harm. [7].

Low-income and marginalized populations also promise to be culturally responsive to the content. Culturally-sensitive AI tools that tailor examples, writing, or stories to culturally-relevant settings can help learners identify with curricula and reduce the sense of cultural alienation that students from historically marginalized or minority backgrounds often experience. This approach aligns with equity-based pedagogical practices and may help overcome structural discrimination in the mainstream curriculum. [28]. It is crucial to note that, AI-based mastery-learning strategies may enhance learner self-efficacy, as students can advance to the next stage once they reach specific levels of comprehension. Mastery-based progression applies explicitly in situations where the learner lacks foundational knowledge, as it eliminates the acquisition of unaddressed misconceptions. Allowing learners to proceed at their own pace, AI services could promote confidence and reduce learned helplessness, an endemic challenge among at-risk students with a long history of academic failure. [13]. Figure 3 below summarizes the AI Tools for at-risk students.

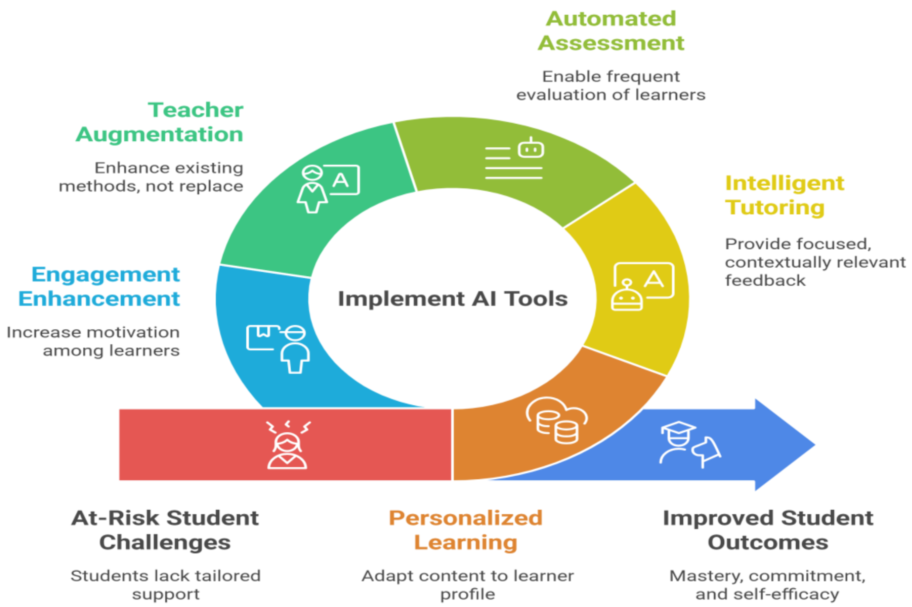

Fig.3 AI Tools for At-Risk Students

IV. IMPLEMENTATION FRAMEWORK AND BEST PRACTICES

4.1. Infrastructure Requirements

The potential of the AI-based education of at-risk students in low-income communities would require efficient and equitable infrastructure. To begin with, one should have access to proper equipment and good internet connectivity. Most AI solutions require at least a basic level of internet connectivity, or periodic connection syncing to cloud services, in areas with low internet connectivity or unreliable power; this is a significant obstacle. According to the world's education authorities, fairness in access to affordable, high-quality connectivity and devices is a precondition for inclusive AI implementation [34, 35]. Technology access solutions could include low-cost hardware and mobile-based platforms, or community-level resource sharing (such as digital laboratories, device pools at schools) to enable participation by individuals who are constrained by personal factors.

It is also essential to choose the right platform. The selection of an AI-based learning system must reflect the socio-economic reality of the target community: lightweight systems that run offline or in a low-bandwidth setting, and require minimal technical support, are the most appropriate. Selection criteria should include device compatibility (e.g., running on basic smartphones), low data usage, use of the native language, and portability for educators and learners with lower digital literacy. Meanwhile, privacy and security of the data should be of primary importance. An AI-based education system usually collects personal data on students, such as performance metrics, behaviour, and even biometric or socio-demographic data, to enable adaptive learning or predictive analytics. Such data might fall into unauthorised hands or be abused without strict precautions in place. Learning institutions are advised to use data governance models that involve the encryption of data in rest and transit, restricting access, anonymisation or pseudonymisation where practicable, and adherence to applicable local or international privacy laws [36, 37, 38]. In addition to technically available safeguards, public policies should exist so that students, families, and communities know what information is gathered, how it is used, and have control over assent and disclosure. The infrastructure requirements are summarized in Table 1 below;

Table 1. Summary of Infrastructure Requirements

Implementation Dimension	Practical Requirement	Risk in Low-Income Contexts	Implication for At-Risk Students
Connectivity	Reliable internet access or offline functionality	Unstable mobile networks; high cost of data	Interrupted learning and limited tool use
Hardware Access	Devices accessible at home or school	Shared devices; low device-to-student ratio	Reduced personalised interaction time
Data Protection	Secure data management and compliance	Weak regulatory capacity and confidentiality breaches	Increased privacy vulnerabilities
Teacher Capacity	Professional development and AI literacy	Limited training budgets and high turnover	Risk of disengagement and inequity
Cultural Adaption	Local language and contextual relevance	Imported content that ignores local realities	Risk of disengagement and inequity
Maintenance & Support	Technical expertise for troubleshooting	Lack of technical personnel	Frequent downtime and tool abandonment

4.2 Pedagogical Integration

Sustainable impact requires careful pedagogical inclusion even when infrastructure is already in place. The most realistic approach may be a blended-learning model that combines human-led instruction with AI-assisted learning. In this model, AI tools do not replace teachers but complement them, offering personalised support, remediation, or enhancement. However, it is the responsibility of teachers to provide social, emotional, and context-based supports to learning. Such a combination preserves the relational aspect of the teaching process, which is particularly essential for at-risk students who might need guidance, support, and contextualization.

A fundamental pillar of a successful integration is teacher training and professional development. Many teachers, especially in low-income or resource-deprived settings, might not be familiar with AI tools or particularly confident about how they could effectively incorporate them into their pedagogy. A well-organized professional development, such as digital literacy, the pedagogical application of AI tools, data interpretation, etc., can enable the teacher to make good use of AI not merely as a curiosity but with a specific aim. The support provided by institutions should be offered not only through work once, but also through a coach, colleagues, and reflection, as these three things contribute to gradual, long-term uptake, rather than superficial, short-term adoption.

There is a need to balance human interaction with AI support. The overuse of automated instruction can become a threat to dehumanise learning or simply put aside other critical teacher-student relationships. Instead, AI can be considered as an aid tool, enabling teachers to spend more time on repetitive activities, introducing differentiated instruction, and performing remediation, but not eliminating human-centered processes such as discussion, critical thinking, social learning, and emotional support. This balance ensures that the strengths of both humans and machines are maximised, while the weaknesses of the two are minimised.

4.3 Equity-Centered Design Principles

Equity-based design should also be applied to every phase of development and deployment to prevent the worsening of the current inequalities by AI interventions. First, the problem of algorithmic bias should be addressed preemptively. The problem with AI models trained on data that over-represents a particular demographic or linguistic group is that they may act in a discriminatory manner, perhaps with worse performance for students from underrepresented backgrounds, or perpetuate historical inequities. ExAI implementing systems must be trained on diverse, representative data, use bias-aware machine learning methods, and undergo regular bias audits [38, 39, 40]. Accountability and trust among stakeholders are also facilitated by transparency, which is the explainability of the process through which recommendations or other adaptations are made.

It is also important to ensure it is culturally relevant and responsive. The language, examples, content, and teaching strategies must align with the learners' cultural and social backgrounds. AI tools developed in high-income or culturally divergent contexts need to be localized frequently, i.e., through language translation, alignment with local curriculum, culturally significant context, and analogies, to

International Journal of Engineering Applied Sciences and Technology, 2025
Vol. 10, Issue 08, ISSN No. 2455-2143, Pages 48-58
Published Online December 2025 in IJEAST (http://www.ijeast.com)

ensure that the learner can relate to, comprehend, and engage with them. Student access should also include accessibility for students with disabilities. There is some potential in AI-driven technology to help in this aspect, such as text-to-speech, speech recognition, controllable speed, and multimodal content. However, it would be necessary to make the developers willing and able to design around this inclusivity. Educational systems that have used AI should make accessibility features more than just the conclusion of the design, ensuring that secondary learners with visual, hearing, cognitive, or motor disabilities are not left out.

4.4 Stakeholder Engagement

Anthropometric involvement of all concerned stakeholders, such as students, families, and communities, educators, and policymakers, to integrate AI successfully and ethically is the key to the success in AIs. In low-income settings, community participation is essential, and trust, social behavior, and resource sharing are known to determine its adoption and maintenance. The involvement of community leaders, parents, and local stakeholders at the initial stages is known to facilitate ensuring that the intervention meets local values, addresses real needs, and receives communal support. Design and implementation should be guided by the voices of students themselves. The sense of ownership, relevance, and responsiveness is achieved through participatory design, where learners provide feedback, share what they like and dislike about the content, interface, language, and pacing, and raise concerns. It can be used to make AI tools adopted regularly, efficiently, and sustainably, rather than leaving them after the initial novelty. The literature on human-centred AI in education provides the essentials for engaging end users (students and teachers) at every phase of system design and implementation [41, 42]. Another important aspect is family involvement, especially in cases where the learners are underage. The parents and caregivers need to be educated about the data they gather, how the AI platform will operate, the advantages and risks it presents, and how they can help their children properly use such tools. Providing basic community training or informational sessions on AI tools may increase trust and uptake when digital literacy is low, and stakeholders worry about privacy or misuse.

V. CASE STUDIES AND EVIDENCES

A case in point is a recent longitudinal study carried out in Ghana, where an AI-enabled conversation tutor named Rori was introduced to eleven schools with low-income, resource-limited approaches to students. In this programme, students in third through ninth grade communicated with Rori via simple mobile phones in two 30-minute sessions a week, which they combined with regular classroom lessons. Within eight months, the treatment group showed a statistically significant improvement in mathematics performance compared to the traditional modalities-only group of peers. The effect size in the study is 0.37 ($p < 0.001$), indicating moderate improvements in math performance. This observation is fascinating as Rori can be run on a relatively limited hardware and designed to operate across low-bandwidth networks - an environment that characterizes many under-resource countries (LMIC) contexts - and, as a result, the practicability of scalable AI-based tutoring in low-resource settings has been shown [25, 43].

The second example about the use of predictive analytics modelling was recently reported in the context of the Moroccan Ministry of National Education, which focused on students with high attrition risk before graduation. The system used machine-learning algorithms and historical student data to predict the risk of dropping out. The model was found to predict well, with 88 per cent accuracy, 88 per cent recall, 86 per cent precision, and an area under the receiver operating characteristic curve (AUC) of 87 per cent. These results demonstrate that AI may be used to detect at-risk learners early, a prerequisite step in the timely intervention and retention process. The strategy is especially relevant to low-income communities, and dropout rates are often worsened by socioeconomic and resource-related factors [44]. Combined, these two examples such as AI-tutoring as academic assistance, and AI-inspired early warning to avoid school dropout, provide similar approaches helping vulnerable learners: one would improve study performance, and the other would allay the disengagement and dropout.

In addition to the single-case searches, the meta-analytical results are a bigger picture of the impact of AI on education. The most recent systematic review investigating the effectiveness of intelligent tutoring systems (ITS) included 28 K-12 studies comprising 4,597 participants. It was found in the review that positive impacts on learning and performance were generally observed compared to traditional instructions, though a trim level of gain was noticed when compared to non-intelligent (non-AI) tutoring systems and great diversity was observed amongst various contexts. These results are hopeful and at the same time indicate the need to conduct more context-sensitive and rigorous studies especially in low-income and resource-limited settings where infrastructure, access, and external socioeconomic variables have the potential to moderate the results [26, 45].

The other indicators which are appropriate and happen to be empirically based are cost-effectiveness and scalability. As seen in the Ghanaian case with Rori, the utilization of simple mobile phones as opposed to computers and the need to address low-bandwidth situations significantly addressed the barriers to infrastructure, which is a critical strength in most LMICs. In addition, the current relatively low per-student price-tag of AI tutoring (when used on large-scale intervention) means that these interventions might be cost effective when applied to large groups of disadvantaged learners. Modern research highlights the idea that AI-based solutions are both useful and scalable, especially in the availability of conventional, resource-intensive interventions (e.g., small groups tutoring, in-person remedial courses) are not feasible or affordable [46, 47].

But there are gaps also which are defined by extant evidence. Most experimental and quasi-experimental research is conducted in settings with relatively well-developed infrastructure or digital connectivity; the truly under-resourced rural or informal settlements are the true under-represented. Little longitudinal information exists regarding the long-term benefits of learning, student retention, and life overall. Also, the difference in effect sizes among the studies implies the presence of contextual characteristics, including quality of implementation, frequency of use, combination with human support and socioeconomic factors, which affect the overall effectiveness. Overall, early indications of successful applications in real-world settings as well as systematic research suggest that AI could become helpful in benefiting at-risk students in low-income communities, not only academically but also allowing dropouts to be noticed. However, the perceived novelty of most interventions and the lack of completion in coverage of research highlight the urgency of more rigorous, contextual, and long-term research to build the information base to guide policy and practice.

VI. RECOMMENDATION ON POLICIES AND FUTURE PROTECTIONS

Governments and international development agencies need to at the policy level to focus on specific streams of funding specifically to facilitate AI infrastructure to support low-income education systems such as affordable connectivity, open-source platforms and fair device acquisitions. Regulatory frameworks that establish regulatory rules on how such data can be collected and targeted to ensure fair, transparent, and safe use of algorithms should govern such investment. In concurrence, education administrations respectively ought to establish equity-focused AI policies that compel technology vendors to exhibit quantifiable gains concerning accessibility to at-risk learners so that market-driven adoption will not reinforce conventional inequalities. Greater international collaboration especially using multilateral development institutions may help harmonize the levels of ethics and promote learning between low-income areas that have common structural impediments.

At the institutional level, the implementation roadmaps that must be implemented in individual schools and in the districts should be sequenced with the distinct pedagogical goals and constant assessment. Professional development strategies are needed to be guaranteed so that teachers obtain the skills required to process AI-generated learning analytics and learn how to integrate adaptive feedback into teaching. Cooperation with local civil associations, community groups, and telecommunication companies can reinforce the partnership with parents, neither isolate AI application nor make it culturally insensitive. Further investigations need to probe under-researched areas and population groups, tackle the doctor of methodological weaknesses in the existing literature, such as a lack of longitudinal support and limited empirical studies in low-resource settings and analysis of contextual factors. The long-term interdisciplinary collaboration is the pillar to continue achieving responsible and equitable implementation of AI in education.

VII. CONCLUSION

The above discussion has highlighted how AI technologies can redefine immense opportunities in increasing access to education among the at-risk pupils in low-income communities. In the recent literature, AI-based personalized learning, adaptive tutoring systems, automated feedback systems, and predictive analytics have proven to reduce learning shortfalls that arise out of structural inequality. Simultaneously, the evidence also demonstrates clearly that such technologies are the ones that cannot be considered panaceas. They should be based on infrastructure preparedness, the participation of teachers, and purposeful equity-oriented design. Despite the great opportunities of AI, the issue of ethics is still unresolved, revealing numerous ethical issues related to privacy, surveillance, and algorithmic bias, which makes it vital to move forward with its implementation only carefully and regarding the context. However, the broader implication here is that correctly designed AI systems might help marginalized learners enjoy the quality of instruction that they could not get previously because of the lack of resources. Educators, policymakers and researchers should therefore combine efforts in making sure that the decision to invest in specific areas and reform certain curriculum and the regulatory environment are made through the lens of inclusiveness and social justice. Empirical studies on the long-term effects of learning should be further pursued and the research ought to be applied in underserved settings. Finally, altruistic adoption means long-term devotion to the equilibrium between innovation and ethical awareness, therefore making sure that AI can add value to the educational equity in the world, instead of strengthening the current boundaries.

Conflict of Interest
There was no conflict of interest

VIII. REFERENCE

[1]. Azoulay A. (2024). 251M children and youth still out of school, despite decades of progress, UNESCO Press Release. URL: https://www.unesco.org/en/articles/251m-children-and-youth-still-out-school-despite-decades-

progress-unesco-report

[2]. Azoulay A. (2024). Out-of-school children and educational gaps cost the global economy $10,000 billion a year, UNESCO Article. URL: https://www.unesco.org/en/articles/out-school-children-and-educational-gaps-cost-global-economy-10000-billion-year

[3]. Montoya S. (2023). Education financing and SDG 4 progress, UNESCO Institute for Statistics / GEM Report. URL: https://www.unesco.org/sdg4education2030/en/education-financing

[4]. Azoulay A. (2021). Inclusion and Education: 2020 Global Education Monitoring Report, UNESCO GEM Report. URL: https://gem-report-2020.unesco.org/thematic

[5]. Azoulay A. (2020). Inclusion in education and support gaps during COVID-19, UNESCO Article. URL: https://www.unesco.org/en/articles/unesco-report-inclusion-education-shows-40-poorest-countries-did-not-provide-specific-support

[6]. Ilie S., Rose P. (2016). Is equal access to higher education in South Asia and sub-Saharan Africa achievable by 2030?, Higher Education, 72(4), pp. 435–455. DOI: https://doi.org/10.1007/s10734-016-0039-3

[7]. Garzón J., Patiño E., Marulanda C. (2025). Systematic review of artificial intelligence in education, Multimodal Technologies and Interaction, 9(8), p. 84. DOI: https://doi.org/10.3390/mti9080084

[8]. Katona J., Ida K. (2025). AI-based adaptive programming education for socially disadvantaged students, TechTrends. DOI: https://doi.org/10.1007/s11528-025-01088-8

[9]. Iqbal S. (2024). Artificial intelligence in education: Transforming pedagogical practices, AI EDIFY Journal, 1(4), pp. 10–18. URL: https://researchcorridor.org/index.php/aiej/article/view/249

[10]. Hariyanto, Kristianingsih F.X.D., Maharani R. (2025). Artificial intelligence in adaptive education, Discover Education, 4(1). DOI: https://doi.org/10.1007/s44217-025-00908-6

[11]. Tapalova O., Zhiyenbayeva N. (2022). AIEd for personalised learning pathways, Electronic Journal of e-Learning, 20(5), pp. 639–653. DOI: https://doi.org/10.34190/ejel.20.5.2597

[12]. Liu V., Latif E., Zhai X. (2025). Advancing education through tutoring systems: A systematic review. URL: https://www.researchgate.net/publication/389821399

[13]. Choi J.H., Garrod O., Atherton P., Joyce-Gibbons A., Mason-Sesay M., Björkegren D. (2023). Are LLMs useful in the poorest schools?, arXiv. DOI: https://doi.org/10.48550/arxiv.2310.02982

[14]. CollegeNP Editor. (2025). Rural education problems: Challenges and solutions. URL: https://www.collegenp.com/article/rural-education-problems-challenges-solutions

[15]. Montoya S. (2024). Monitoring SDG 4: Progress and challenges, Global Education Monitoring Report. URL: https://www.unesco.org/reports/gem-report/en/2024-monitoringsdg4

[16]. Worku M.Y. (2025). Access-equity tensions in education, Social Sciences & Humanities Open, 11, p. 101443. DOI: https://doi.org/10.1016/j.ssaho.2025.101443

[17]. Kushariyadi, Mustofa, Permatasari A., Fitriani N.A., Faridah L. (2024). Technology in inclusive education, IJERE, 3(2), pp. 854–861. DOI: https://doi.org/10.55299/ijere.v3i2.1132

[18]. University of Arts and Culture Editorial Team. (2024). Challenges of implementing educational technology in developing countries. URL: https://en.unsibu.ac.id/the-challenges-of-implementing-educational-technology-in-developing-countries

[19]. Kennedy G.M. (2025). Digital inclusion in Liberia's education sector, American Journal of Educational Research, 13(3), pp. 102–110. DOI: https://doi.org/10.12691/education-13-3-1

[20]. Khana R.W., Ahmad M. (2025). Equity and inclusion in modern education systems. URL: https://ijssa.com/index.php/ijssa/article/view/470/371

[21]. Gunawardena M., Bishop P.A., Aviruppola K. (2024). Personalized learning, Teaching and Teacher Education, 139, p. 104429. DOI: https://doi.org/10.1016/j.tate.2023.104429

[22]. Main P. (2021). Zone of proximal development: A teacher's guide. URL: https://www.structural-learning.com/post/the-zone-of-proximal-development-a-teachers-guide

[23]. Roski M., Sebastian R., Ewerth R., Hoppe A., Nehring A. (2024). Learning analytics and UDL, Computers & Education, 214, p. 105028. DOI: https://doi.org/10.1016/j.compedu.2024.105028

[24]. Lin C.C., Huang A.Y.Q., Lu O.H.T. (2023). AI in intelligent tutoring systems, Smart Learning Environments, 10(1). DOI: https://doi.org/10.1186/s40561-023-00260-y

[25]. Sevilla A., Cuevas-Ruiz P., Rello L., Sanz I. (2025). AI-guided tutors and computer-assisted learning, Italian Economic Journal. DOI: https://doi.org/10.1007/s40797-025-00354-1

[26]. Létourneau A., Martineau D., Charland P., Karran

J.A., Boasen J., Léger P.M. (2025). AI-driven ITS in K-12 education, npj Science of Learning, 10(1), pp. 1–13. DOI: https://doi.org/10.1038/s41539-025-00320-7

[27]. Villegas-Ch W., Buenano-Fernandez D., Navarro A.M., Mera-Navarrete A. (2025). Adaptive intelligent tutoring systems for STEM, Smart Learning Environments, 12(1). DOI: https://doi.org/10.1186/s40561-025-00389-y

[28]. Melo-López V.A., Basantes-Andrade A., Gudiño-Mejía C.B., Hernández-Martínez E. (2025). AI and inclusive education, Education Sciences, 15(5), p. 539. DOI: https://doi.org/10.3390/educsci15050539

[29]. Sajja R., Sermet Y., Cikmaz M., Cwiertny D.M., Demir İ. (2023). AI-enabled intelligent assistant for adaptive learning, arXiv. DOI: https://doi.org/10.48550/arxiv.2309.10892

[30]. Younas M., Abdel D., Noor U. (2025). Impact of AI-based learning tools, Frontiers in Education, 10. DOI: https://doi.org/10.3389/feduc.2025.1689205

[31]. Luo J., Zheng C., Yin J., Teo H.H. (2025). AI-based learning tools in higher education, IJETHE, 22(1). DOI: https://doi.org/10.1186/s41239-025-00540-2

[32]. Memari M., Ruggles K. (2025). Artificial intelligence in elementary STEM education, arXiv. DOI: https://doi.org/10.48550/arxiv.2511.00105

[33]. Zawacki-Richter O., Marín V.I., Bond M., Gouverneur F. (2019). AI applications in higher education, IJETHE, 16(1), pp. 1–27. DOI: https://doi.org/10.1186/s41239-019-0171-0

[34]. OECD Editor. (2023). OECD digital education outlook 2023. URL: https://www.oecd.org

[35]. SIIT Editor. (2025). Education technology for remote learning equity. URL: https://siit.co/blog/education-technology-for-remote-learning-equity/49439

[36]. Ashikuzzaman Md. (2023). Privacy and data security in AI-enabled higher education. URL: https://www.lisedunetwork.com/addressing-privacy-and-data-security-concerns-in-the-integration-of-ai-in-higher-education

[37]. Kelso E., Soneji A., Rahaman S., Soshitaishvili Y., Hasan R. (2024). Privacy and security hurdles in education technology acquisition, arXiv. DOI: https://doi.org/10.48550/arxiv.2405.11712

[38]. Mehmood T. (2025). Ethical AI in education, AI EDIFY Journal, 2(1), pp. 38–45. URL: https://www.researchcorridor.org/index.php/aiej/article/view/247

[39]. Li J., Huang Q. (2025). Ethical dilemmas in AI-enhanced education, International Journal of Knowledge Management, 21(1), pp. 1–21. DOI: https://doi.org/10.4018/IJKM.382384

[40]. Vidyadhari C.S., et al. (2024). FairAIED: Fairness, bias, and ethics in educational AI, arXiv. DOI: https://doi.org/10.48550/arxiv.2407.18745

[41]. Alfredo R., et al. (2023). Human-centred learning analytics and AI in education, arXiv. URL: https://arxiv.org/abs/2312.12751

[42]. Li M., Gao L. (2025). Challenges of AI integration in education, IJRISS, IX(IIIS), pp. 6109–6116. DOI: https://doi.org/10.47772/ijriss.2025.903sedu0441

[43]. Henkel O., Horne-Robinson H., Kozhakhmetova N., Lee A. (2024). AI tutor impact on math achievement in Ghana, arXiv. URL: https://arxiv.org/abs/2402.09809

[44]. Elbouknify I., et al. (2025). AI-based identification and support of at-risk students, arXiv. DOI: https://doi.org/10.48550/arxiv.2504.07160

[45]. Eling F., Ogwal A. (2025). Bridging learning gaps using AI-powered technologies, IJRISS, IX(IIIS), pp. 2011–2016. DOI: https://doi.org/10.47772/ijriss.2025.903sedu0155

[46]. Tripathi A., Yadav V., Kumar S. (2025). AI for rural education, Preprints.org. DOI: https://doi.org/10.20944/preprints202504.0598.v1

[47]. Leong W.Y. (2024). Transforming rural and underserved schools with AI-powered education solutions, ASM Science Journal, 19, pp. 1–12. DOI: https://doi.org/10.32802/asmscj.2023.1895

IJEAST

INTERNATIONAL JOURNAL
OF ENGINEERING APPLIED SCIENCE AND TECHNOLOGY

ABOUT IJEAST

International Journal of Engineering Applied Science and Technology (IJEAST) is a peer-reviewed, open access journal that publishes high-quality research papers in the field of Engineering, Applied Science and Technology.

IJEAST aims to provide a platform for researchers, academicians, and professionals to share their innovative ideas, research findings, and practical experiences with the global scientific community.

FOCUS AREAS

- Engineering
- Applied Science
- Technology
- Innovation & Development
- Interdisciplinary Studies

PEER REVIEWED
All submissions are rigorously peer reviewed to ensure quality.

OPEN ACCESS
Free and unrestricted access to research for all.

GLOBAL REACH
Connecting researchers and professionals worldwide.

TIMELY PUBLICATION
We ensure a swift and efficient publication process.

For more information, visit our website
www.ijeast.com

INTERNATIONAL JOURNAL
OF ENGINEERING APPLIED SCIENCE AND TECHNOLOGY

editor@ijeast.com
www.ijeast.com
India

2455-2143