

Bridging the Gap: Defining the Problem Space for AI-Driven Personalized Learning in Global Education

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Abstract: Achieving Sustainable Development Goal 4 (SDG 4) requires a fundamental shift in how educational resources are distributed and personalized, particularly in Low- and Middle-Income Countries (LMICs). This paper defines the problem space for AI-driven personalized learning by conducting a systematic review of existing technologies and their limitations in resource-constrained settings. Through a synthesis of literature (2013–2024) and an analysis of large-scale datasets including EdNet (131M interactions), OULAD, and Khan Academy, this research identifies a critical gap: the lack of scalable, context-aware AI frameworks that prioritize cultural localization and low-resource resilience. The findings suggest that while AI offers transformative potential for engagement, current solutions remain hindered by infrastructure dependency and algorithmic bias.

Keywords: Artificial Intelligence in Education (AIED), Personalized Learning Systems, Educational Technology in LMICs, Intelligent Tutoring Systems, Intelligent Tutoring Systems.

1. Introduction

1.1. Background and Motivation

The global education system still has a lot of unfairness that makes it hard for everyone to learn equally, especially in lower- and middle-income countries (LMICs). Problems like too many students in a classroom, not enough qualified teachers, and not enough access to good learning materials, especially in rural areas, slow down students' progress and success. Digital technologies and AI-driven educational tools present potential solutions via personalized and timely learning assistance; however, their efficacy is contingent upon advancements in pedagogy, infrastructure, and inclusive system design [4], [5], [1], [2], [3].

1.2. The digital divide in global education

The digital divide is still a big problem for AI-powered personalized learning in education around the world. Students' ability to use AI-based educational tools depends on how easy it is for them to get devices, connect to the internet, and learn at home. If these technologies are made mainly for places with a lot of money, they might not work well in places with few resources, which would make educational inequalities even worse. So, for AI in education to be fair, it needs to focus on inclusive design, privacy, transparency, fairness, scalability, and local relevance to make sure that all types of learners can benefit from it [2],[4].

1.3. AI as personalized learning

AI is a great tool for personalized learning because it can change educational content in real time to meet the needs of each learner. AI and machine learning support a wide range of tools, including chatbots and virtual assistants that give instant help, automated grading systems that give feedback on time, personalized language learning platforms with speech recognition, smart course recommendation systems that suggest courses based on how well a student is doing, and AI-driven STEM simulations that

make hard ideas easier to understand and more fun to learn. These technologies work together to improve engagement, speed up learning, and overall mastery.

1.4. Problems and trade-offs

Even though AI has a lot of potential in education, there are still a lot of problems that need to be worked out. Some of the most important issues are ethics, data privacy and security, algorithmic bias, and the possibility of making educational inequalities worse if systems aren't designed to be inclusive. Practical problems that make it hard to implement effectively include the need for educator training, the ability to work with existing technologies, and the ability to scale across different education systems. Also, governance and policy that are in line with the curriculum, quality assurance, and accountability are all important to make sure that AI helps learning. Consequently, inclusive design, transparency, and ongoing assessment are essential for the responsible implementation of AI in education [4], [2], [3].

1.5. Objectives, Contributions, and Structure of the Paper

This paper describes the problem space of AI-driven personalized learning in global education by analyzing the advantages and constraints of AI-based personalization in various educational settings, especially in LMICs. It suggests design principles for AI learning systems that are inclusive and protect privacy, make them easier to use, and lower algorithmic bias. It also suggests a way to judge AI-driven learning based on how well it teaches, how fair it is, and how easy it is to scale.

The paper looks at how AI is being used in schools right now, how the digital divide affects AI-based learning outcomes, and how to make AI-based learning more inclusive. It also talks about the problems that come up when trying to implement AI-based learning and gives suggestions for responsible use and future research.

2. Related work

2.1 AI in Personalized Learning

AI-enabled personalized learning changes the content of lessons for each student based on how well they are doing and in real time changes the level of difficulty, the order of the lessons, and the feedback [1],[3]. Smart tutoring systems and learning analytics are two examples of technologies that can help find students who are at risk, support targeted interventions, and boost engagement and academic performance [6]. AI systems can model learning trajectories and give timely advice by using large amounts of educational data and keeping track of how students interact with each other over time. However, to make it work well, there needs to be enough infrastructure, teachers who are ready, and design that works for everyone to make sure everyone gets the same benefits [7],[8].

2.2 Analysis of Educational Datasets

- **EdNet:** The largest public dataset, capturing 131,441,538 interactions from 784,309 students. Its hierarchical structure records actions from simple question-solving to complex video consumption behaviors [9].
- **OULAD (Open University Learning Analytics Dataset):** Provides critical demographic context, including the Index of Multiple Deprivation (IMD), which helps identify vulnerable students at early stages [6].
- **Khan Academy:** Offers a benchmark for Socratic-style tutoring, focusing on the AI's ability to provide constructive feedback without directly giving answers [9].
- **ASSISTments:** A widely used dataset for modeling student knowledge and predicting performance trends [9].

2.3 Equity and Implementation Challenges

The literature identifies several obstacles to the adoption of AI in education within LMICs, notably insufficient digital infrastructure, inconsistent internet connectivity, and inadequate levels of digital literacy. These things make a digital divide that affects who can use AI-powered learning tools [1][3]. If local limitations, privacy, and governance issues are not taken into account, systems that are mostly made for well-off settings may not work well in LMIC contexts. Also, AI models that were trained on small or biased datasets may give different results for different groups of learners. Researchers advocate for inclusive design, privacy protection, transparency, and ongoing evaluation [5].

3. Methodology

This paper utilizes a systematic literature review and synthesis methodology to define the current research landscape and identify implementation barriers.

3.1 Search Strategy and Identification

The research involved a comprehensive search across major academic databases, including IEEE Xplore, Scopus, ScienceDirect, SpringerLink, and Google Scholar. The search focused on peer-reviewed articles published between 2013 and 2024, with a targeted search period of 2020–2025 for recent advancements in Generative AI. Key search terms included "AI in education," "personalized learning," "inclusive AI," and "intelligent tutoring systems".

3.2 Inclusion and Exclusion Criteria

To ensure relevance and rigor, the following criteria were applied:

- **Inclusion:** Peer-reviewed studies focusing on AI/ML in education, adaptive learning environments, educational equity, and implementations in LMICs aligned with SDG 4.
- **Exclusion:** non-English publications, papers without a clear educational application, purely technical AI papers lacking pedagogical context, and non-peer-reviewed content such as blog posts.

4. Analysis and Synthesis

Based on the systematic review, the following domain-level table encapsulates the identified strengths and practical barriers of AI in personalized learning, along with external references that support each domain.

Table 1. Comparative Overview of AI Strengths and Barriers in Personalized Learning

Domain	Strengths of AI Solutions	Current Limitations and Barriers
Pedagogy	Tailored experiences; real-time feedback; identification of knowledge gaps.	Lack of teacher/student involvement in design; risk of "one-size-fits-all" defaults. [10], [11], [12], [13]
Technical	High predictive accuracy; adaptive pathing.	Infrastructure-heavy; high cost of cloud computing; limited multilingual support. [10], [11], [12], [13]
Ethics	Potential to support students with disabilities through accessibility features.	Data privacy concerns; algorithmic bias; lack of transparency in "black box" models. [10], [11]

5. Discussion: Identifying Research Gaps

The synthesis shows that AI can help with engagement, but there is a "critical gap" for scalable, context-aware frameworks that put equity first. Most current studies concentrate on binary classification (Pass/Fail) instead of longitudinal development across varied socio-economic contexts. There is an immediate necessity for "Expert-in-the-Loop" frameworks that enable educators to serve as active collaborators in the adaptation of AI, guaranteeing that AI-generated material aligns with regional curricula and cultural standards.

Conclusion

This paper outlines the challenges in the realm of AI-driven learning by pinpointing the infrastructural, cultural, and ethical obstacles encountered by LMICs. To meet SDG 4, future research and development must go beyond just making sure that systems are technically accurate. It must also focus on "resilient" architectures, like Edge AI and metadata prioritization, that can work in environments with limited bandwidth. The Lincoln Global Postdoctoral Programme's goal is to move from this problem definition to a tested framework that "makes the world smaller so that learning can actually be larger".

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