

Advancing the Framework for Inclusive AI-Driven Personalized Learning: Multi-Phase Validation and Modeling Approaches

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Abstract: Artificial Intelligence (AI) offers strong potential to enhance personalized learning, but its implementation in low- and middle-income countries (LMICs) is limited by infrastructure constraints, ethical concerns, and lack of context-aware frameworks. This study proposes and validates an inclusive framework for AI-driven personalized learning aligned with Sustainable Development Goal 4 (SDG-4). A multi-phase methodology is used, combining expert consensus through the Delphi method with simulation-based modeling using large-scale educational datasets such as EdNet and OULAD. The findings highlight the importance of resilient architectures like Edge AI for low-connectivity environments and emphasize Expert-in-the-Loop governance to ensure culturally relevant, multilingual, and ethical AI deployment. The framework integrates pedagogical, technical, ethical, and inclusivity dimensions to support scalable and equitable AI-enabled learning in resource-constrained contexts.

Keywords: Artificial Intelligence in Education (AIED), Personalized Learning Systems, Edge AI in Education, Educational Equity in LMICs, Learning Analytics and Knowledge Tracing.

1. Introduction

1.1. Background and Motivation

The global effort to ensure equitable quality education remains hindered by deep-seated disparities in resource distribution, particularly in LMICs, where AI-enabled learning must contend with infrastructural gaps, connectivity limitations, and governance barriers [1]. While Artificial Intelligence (AI) and Machine Learning (ML) offer transformative potential for personalized learning, their deployment is often stalled by a reliance on infrastructure-heavy, Western-centric models that overlook local connectivity realities and cultural contexts [2], [3].

Initial research identified a "triad of knowledge gaps" that prevents the effective deployment of AIED (AI in Education):

- **Suitability Gap:** Current AI tools often require high-bandwidth connectivity and advanced hardware, making them unsuitable for off-grid or rural environments [4].
- **Ethical Gap:** A systemic failure to address algorithmic bias and data privacy risks within centralized cloud architectures.
- **Inclusivity Gap:** A lack of context-aware frameworks that integrate local languages and regional cultural norms [4], [5]. These gaps align with broader calls for inclusive, participatory AI design and governance that foreground local ownership and capability-building [5].

This paper advances research from problem definition to technical validation. The objective is to design and test a conceptual framework for inclusivity and scalability that aligns with SDG-4 targets, ensuring that AI-driven personalization empowers rather than excludes marginalized learners. AI-for-SDG

discussions emphasize both the enabling potential of AI for education and the need to address equity, governance, and data-privacy considerations to realize this potential across diverse contexts [3], [1].

2. Related work

2.1 Personalized Learning and AIED Benchmarks

AI-enabled personalized learning systems adapt instructional difficulty, pacing, and feedback in real time based on learner performance. The effectiveness of these systems depends largely on the quality and representativeness of the training data [6]. Large-scale benchmark datasets such as EdNet and the Open University Learning Analytics Dataset (OULAD) are widely used to analyze student interactions and model learning behaviors. These datasets support research on learning trajectories, feedback strategies, and knowledge tracing, and are also used in frameworks like GenAI-EduNet for model training and evaluation [7]. In addition, literature highlights key ethical and governance concerns—such as privacy, fairness, transparency, and trust—which influence the adoption and responsible deployment of AI in education. Ensuring equitable and context-aware AI design is therefore essential for aligning AI-driven personalization with broader educational goals and SDG priorities [8].

2.2 Framework Validation Methodologies

Validating educational AI frameworks often combines expert judgment with evidence-based analysis. The Delphi method is widely used to achieve expert consensus in educational technology research, especially in contexts such as LMICs where empirical data may be limited [9]. Through iterative rounds of expert consultation, Delphi processes help identify design principles, governance requirements, and policy recommendations for AI integration in education [10].

A notable example is the Design-Delphi approach proposed by Eyal and Ronit [10], which provides a structured four-phase framework—planning, design, validation, and deployment—for integrating AI into educational assessment [10]. Similar studies use Delphi techniques to identify competencies, training needs, and pedagogical practices for teachers and policymakers. However, researchers note that Delphi findings mainly reflect expert opinion rather than causal evidence, making it important to combine them with data-driven validation and iterative evaluation processes [9]. Together, these approaches support the development of inclusive and governance-aware AI in education frameworks [8].

3. Methodology

This research employs a multi-phase technical approach to validate the proposed inclusive AI framework.

3.1 Phase I: Expert Validation (Delphi Method)

The conceptual design is first validated using a modified e-Delphi technique to accommodate geographically dispersed specialists [11].

- **Expert Selection:** A panel of 20 to 30 experts is selected across domains including AI design, pedagogy, and LMIC policy [11].
- **Iterative Rounds:**
 - **Round 1:** Open-ended inquiries to identify critical indicators of inclusivity and technical feasibility [11].
 - **Round 2:** Structured Likert-scale questionnaires where experts rate items based on their relevance to SDG-4 [11].
 - **Round 3:** Controlled feedback where experts reconcile disagreements, aiming for a consensus threshold of agreement [11].

3.2 Phase II: Simulation and Modeling

The framework's predictive and adaptive capabilities are tested through simulations across diverse educational datasets [12].

- **Knowledge Tracing:** Using EdNet, we simulate learning path recommendations to measure how the framework adjusts difficulty sequences to prevent cognitive overload [12].
- **Risk Modeling:** Utilizing OULAD, the research employs algorithms like Random Forest (which has shown accuracies up to) to identify "at-risk" students based on demographic and engagement data [13].
- **Feedback Loops:** Data from Khan Academy and ASSISTments is used to model the framework's ability to provide Socratic feedback, ensuring that the AI supports mastery-based learning rather than rote memorization [13].

4. Discussion

4.1. Resilient Architectures: Edge AI vs. Cloud

A key implication from the analysis is the importance of edge-based AI architectures for education in LMIC contexts. Edge AI enables local processing and on-device inference, reducing dependency on constant internet connectivity and centralized cloud infrastructure. This approach supports multilingual and culturally contextualized learning environments where connectivity, latency, and data governance are critical concerns [14]. Studies from regions such as the Arab world, Ghana, and India highlight the need for AI tools that align with local languages, curricula, and governance structures. These findings suggest that locally adapted AI solutions may be more effective and equitable than relying solely on cloud-based systems.

4.2 Expert-in-the-Loop (EITL) Governance

The validation process also emphasizes the role of Expert-in-the-Loop (EITL) governance, where educators and domain experts actively collaborate in the design and evaluation of AI systems. Their involvement helps ensure that AI-generated learning materials align with local curricula, cultural norms, and linguistic contexts [15]. Research in LMIC settings also highlights concerns related to privacy, misinformation, and ethical AI deployment, reinforcing the need for transparent and accountable governance frameworks [14]. However, experts note that consensus-based approaches should be complemented with empirical data and pilot testing to avoid over-reliance on expert opinion in data-limited contexts [13].

Table 1. Summary of Framework Dimensions

Dimension	Validation Strategy	Target Outcome
Pedagogical	Delphi Consensus	Scaffolded Master (ZPD) [12]
Technical	EdNet Simulation	Low-Latency Edge Inference [12]
Ethical	OULAD Risk Analysis	Bias-Free Intervention [12]
Inclusivity	Expert Interviews	Multilingual & Localized Content [12]

Conclusion

This second phase of research moves from defining the problem space to a validated, context-aware framework for AI-driven personalized learning. By prioritizing resilient architectures and expert-led validation, the framework offers a scalable roadmap for educational equity. To meet the targets of SDG-4, future development must go beyond technical accuracy to focus on "soulware"—technology that supports human dignity, local culture, and universal access. The final model seeks to make the world smaller so that the potential for learning can truly be larger.

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