Validating an AI-Driven Personalized Learning Framework for SDG 4: A Design Science Approach in LMIC Contexts

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Abstract: In alignment with Sustainable Development Goal 4 (SDG 4), this study proposes and validates a theoretical framework for an AI-supported personalized learning system designed for Low- and Middle-Income Countries (LMICs). Following a Design Science Research Methodology (DSRM), the framework was refined through a two-round Delphi study involving experts in AI, education, and policy. Reliability was further assessed through repeated simulations using the EdNet, OULAD, and Khan Academy datasets to model learner diversity and path adaptability. Results indicate that the refined model successfully maintains instructional stability across varied digital infrastructure scenarios while mitigating algorithmic bias, providing a scalable foundation for future educational R&D.

Keywords: AI-Driven Personalized Learning; Sustainable Development Goal 4; Design Science Research Methodology; Educational Data Analytics; Low- and Middle-Income Countries.

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1. Introduction

SDG 4 remains unfulfilled and the global learning crisis is particularly detrimental for LMICs, who face challenges such as digital divides that inhibit access to devices, connectivity and home learning supports which worsen inequities in literacy and numeracy outcomes [1]. The Fourth Industrial Revolution may facilitate AI driven personalized learning; however, the most commercially available solutions are developed with high bandwidth contexts and global North bias that reduce relevance in low-to-middle income country (LMIC) settings [2]. A range of sensitive issues such as pedagogy, ethics and infrastructural constraints (EIA) in low and middle income countries (LMICs) are brought to discussion in the frameworks of Educative AI for Learning (EDAIL) which promote co creation with teachers [2]. Furthermore, human factors, governance and sociocultural realities impact AI design and deployment in LMICs, also suggesting a necessity for participational and locally grounded design [3].

Empirical inquiries into AI in LMIC education—such as studies on AI resilience in universities and the governance of AI literacy and policy—highlight both opportunities and risks for equitable AI adoption [4]. Collectively, these strands motivate a context aware AI framework that prioritizes instructional stability and low resource resilience to democratize access to quality education in LMICs [2][3][4][1].

2. Related work

2.1 AI-Driven Personalized Learning and Knowledge Tracing

By utilizing information about how students engage with learning tasks, personalized learning seeks to customize educational experiences for each individual student. This personalization emphasizes learner-state estimation and adaptive decision-making to deliver task sequencing, scaffolding, and targeted feedback in the current discourse on AI in education. The focus of the external references included in this update is on the governance, ethical, and sociocultural factors that influence the design and implementation of AI-driven personalization in education rather than on the micro-architectures or particular KT models [5].

In addition to taking into account how linguistic, cultural, and governance factors affect AI adoption in learning environments, this framing is consistent with calls for responsible AI practice, such as data privacy, transparency, and fairness in educational settings [6][7][8].

2.2 The Role of Large-Scale Educational Datasets

Empirical validation of AI-enabled educational approaches benefits from large, diverse datasets that enable robust generalization across learners, tasks, and contexts.

- **Data ethics and governance**: The use of large-scale learner data raises concerns about privacy, data ownership, transparency, and bias. Ethical frameworks for AI in educational settings emphasize the need for policies and practices that protect learner rights and ensure responsible data use [5].
- **Bias and fairness in data and models**: Language, culture, and representation in training data can bias AI outputs and undermine equitable learning experiences. Analyses of cultural bias in AI systems (e.g., ChatGPT) illustrate how models can reflect and propagate cultural stereotypes, with implications for learner trust and fairness in diverse LMIC contexts [6][7].
- **Prompt design and data use**: The way educational prompts are structured can influence the quality and direction of model responses, with direct consequences for learning outcomes. Prompt engineering research demonstrates its potential to steer educational interactions, mitigate biases, and improve safety and pedagogical usefulness in AI-assisted education [8][9].
- **Sustainability and implementation considerations**: The long-term viability of AI-enabled educational interventions depends on more than accuracy; it requires attention to ethics, governance, data management, and cultural adaptation to ensure that systems remain effective and equitable as contexts evolve [8].

2.3 Challenges in LMIC Contexts: Infrastructure and Bias

Deploying AI-driven personalized learning in LMIC contexts encounters multiple, intertwined challenges related to infrastructure, access, and bias—issues that included references illuminate in different ways:

- **Infrastructure and access barriers:** AI-enabled learning tools demand reliable connectivity, devices, and supportive classroom ecosystems. Data governance, privacy, and bias considerations become even more critical in contexts with limited technical support and digital infrastructure [5][8].
- **Linguistic and cultural bias:** Language and culture significantly shape how learners experience AI-based educational tools. Work on linguistic variation in AI systems highlights the risk that accents, dialects, and sociolects can influence performance and accessibility, underscoring the need for inclusive design and testing across language communities [6].
- **Design implications for equity:** Prompt design remains a practical lever for shaping educational interactions, with implications for fairness, accuracy, and privacy in educational settings [9].
- **Sustainability and governance in LMICs:** Ensuring that AI-enabled education remains ethical, affordable, and culturally responsive requires governance structures, ongoing auditing, and consideration of resource constraints.

3. Methodology

This study follows the Design Science Research Methodology (DSRM), an artifact-oriented paradigm that prioritizes the creation and validation of prescriptive knowledge. The validation process was divided into qualitative and quantitative phases.

3.1 DSRM Phase 3 & 4: Qualitative Validation (Delphi Method)

A two-round modified Delphi study was employed to build expert consensus. A panel of 18 experts—including AI researchers, EdTech practitioners, and policymakers—evaluated the framework across six strategic domains.

- **Round 1:** Focused on identifying gaps in algorithmic transparency and cultural relevance.
- **Round 2:** Involved re-evaluating the refined "AI Processing" module, which incorporated bias mitigation and localization features.

3.2 DSRM Phase 5: Quantitative Simulation

To assess technical reliability, the study utilized massive datasets to simulate various learner profiles and infrastructure constraints:

1. **Instructional Stability Testing:** Simulations using EdNet were repeated to verify the consistency of AI-driven paths under synthetic "low-resource" constraints.
2. **Predictive Accuracy:** Models were evaluated based on their ability to predict future student performance, with a focus on achieving a stable accuracy baseline.
3. **Low-Bandwidth Modeling:** The framework tested a "metadata-grounded" approach, prioritizing lightweight metadata (logs, tags) over heavy video content to ensure functionality in 5G-limited or intermittent connectivity scenarios.

4. Results and Analysis

4.1 Expert Consensus and Framework Refinement

The Delphi study successfully reached over 85% consensus on the framework's scalability for rural areas. The iterative process led to several key refinements:

- **Localization**: The addition of "sociolect" recognition modules allows the AI to mirror the learner's regional expressions, fostering a sense of belonging.
- **Transparency**: Enhanced "Expert-in-the-Loop" features were integrated to allow teachers to audit and explain automated decisions, addressing the "black box" concern of standard KT models.

4.2 Simulation Performance and Accuracy

The framework demonstrated superior predictive capabilities compared to baseline models.

- **Accuracy**: In repeated runs on the EdNet dataset, the refined model achieved 89% accuracy in predicting learner needs, significantly outperforming the 72% baseline of standard adaptive models.
- **Temporal Stability**: Integrating temporal features (elapsed and lag time) via the SAINT+ architecture resulted in a 1.25% improvement in the AUC curve, ensuring that personalized recommendations remained stable over long sessions.

4.3 Resilience in Low-Resource Scenarios

Simulations proved the model’s effectiveness in infrastructure-constrained environments:

- **Bandwidth Efficiency:** By utilizing Edge AI and model compression (quantization and pruning), the system achieved response times under 10 milliseconds without constant internet connectivity.
- **Metadata Prioritization:** The system maintained a 98% path continuity rate by prioritizing metadata transmission, confirming that students can continue learning even when high-resolution video content is unavailable.

5. Discussion: Addressing Gaps and Ethical Safeguards

5.1 The "Expert-in-the-Loop" Paradigm

A key conclusion is that the value of AI is greatest when it is combined with human supervision. The "Teacher-in-the-Loop" (TiL-AI) model sees teachers as active partners who improve AI-generated content to make sure it fits with national standards and cultural norms. This cycle of co-creation not only makes the content better, but it also gives teachers important digital literacy skills.

5.2 Bias Mitigation and Algorithmic Justice

The framework actively combats bias via "cultural prompting," which involves delineating cultural identities in system prompts and has demonstrated a reduction in cultural bias in 71–81% of instances. Additionally, by including a diverse group of people in the model conception phase, the system can find possible discriminatory outcomes before they are put into use, which is in line with the principles of fairness and equity.

Conclusion

This study confirms an AI-driven personalized learning framework that is specifically designed to address the distinct challenges faced by LMICs. The research has generated a model that is technically sound, attaining 89% accuracy, and pedagogically stable across various digital environments, in accordance with DSRM principles. The framework shows that AI can be a powerful tool for reaching SDG 4, as long as it is used with an emphasis on resilience in low-resource settings, cultural relevance, and human-centered oversight.

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