AIPLI Hub: A Server-Free Adaptive EdTech Platform Bridging the Learning Equity Gap in Underserved Communities

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Abstract: Learners in Low- and Middle-Income Countries (LMICs) remain excluded from adaptive personalized learning because existing platforms require server infrastructure, stable internet, and English-language proficiency — conditions absent in most underserved schools. This paper introduces AIPLI Hub, a fully browser-native, server-free adaptive learning platform combining Bayesian Knowledge Tracing (BKT) for real-time knowledge state estimation, Gardner's Multiple Intelligence (MI) theory for modality personalization, Explainable AI (XAI) for transparent decision-making, and an IndexedDB persistence layer for offline operation. Expert Delphi validation (n=15) achieved ≥80% consensus on all framework statements; simulation across four benchmark datasets confirmed 90%+ adaptive path consistency and BKT F1-score of 84.9%; a pilot deployment logged 191 sessions across eight multilingual students achieving a 70% class average. AIPLI Hub provides a zero-cost, zero-infrastructure, SDG 4-aligned adaptive learning system deployable immediately in any LMIC school environment.

Keywords: Adaptive Learning; Multiple Intelligence; Offline EdTech; LMIC; SDG 4; Explainable AI.

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1. Introduction

Global EdTech investment exceeded $340 billion in 2023, yet AI-driven adaptive learning platforms have remained inaccessible to the 300 million+ learners in LMICs who lack the server connectivity, high-specification devices, and English-medium instruction these systems require [1]. The problem space underpinning this exclusion was formally characterized in earlier work by the authors [2], which identified the absence of inclusive AI frameworks for LMICs as a critical global gap. Quantitative stakeholder analysis by [3] further confirmed that both educators and policymakers perceive AI integration in assessment as significantly limited by infrastructure, language, and equity barriers. Three structural deficits drive this exclusion: server dependency (existing platforms require continuous cloud connectivity); cognitive homogeneity; and algorithmic opacity. AIPLI Hub is designed to resolve all three deficits through a cohesive architecture grounded in Design Science Research Methodology (DSRM) [3], combining BKT [4][5], Gardner's MI theory [6], and XAI principles within a browser-native IndexedDB data layer.

2. Related work

The theoretical grounding for AIPLI Hub spans three streams. In learning science, [1] established the KLI framework connecting knowledge components to instructional outcomes, underpinning adaptive difficulty sequencing. In knowledge tracing, [8] validated BKT as the most reliable probabilistic method for individual knowledge state modelling. In learning style research, [6] proposed the Multiple Intelligence framework, operationalized for classroom practice by [7]. Nye [9] concluded that ITS deployment in LMICs is constrained by infrastructure intensity, language exclusivity, and absent adaptive frameworks — precisely the gaps AIPLI Hub resolves. Table 1 compares AIPLI Hub against prior systems.

Table 1. AIPLI Hub versus prior adaptive learning systems on LMIC deployment criteria

System	Offline	BKT	MI Profile	XAI	Teacher Dashboard	Ref.
Cognitive Tutor	No	Yes	No	No	Partial	[1]
Deep KT	No	Yes	No	No	No	[8]
Kolibri	Yes	No	No	No	No	[10]
ASSISTments	No	Yes	No	Partial	Yes	[9]
AIPLI Hub (This work)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	—

Key Contribution

- Dual-dimension personalization: First operational system combining BKT knowledge-state difficulty adaptation with [6] eight MI types for delivery modality personalization in a single deployable platform, extending the pedagogical design principles of [7] into a live adaptive engine.
- Zero-infrastructure architecture: A shared browser-native IndexedDB connector (AIPLI_DB.js) persists sessions, MI assessments, BKT states, and student profiles locally — no server, no network request, full offline function, directly addressing the infrastructure barriers identified by [2].
- Longitudinal MI tracking: Every Intelligence Compass assessment is stored as an immutable record, enabling developmental MI profile evolution tracking over an academic year — a research capability absent from all prior EdTech deployments reviewed by [9].

3. Methodology

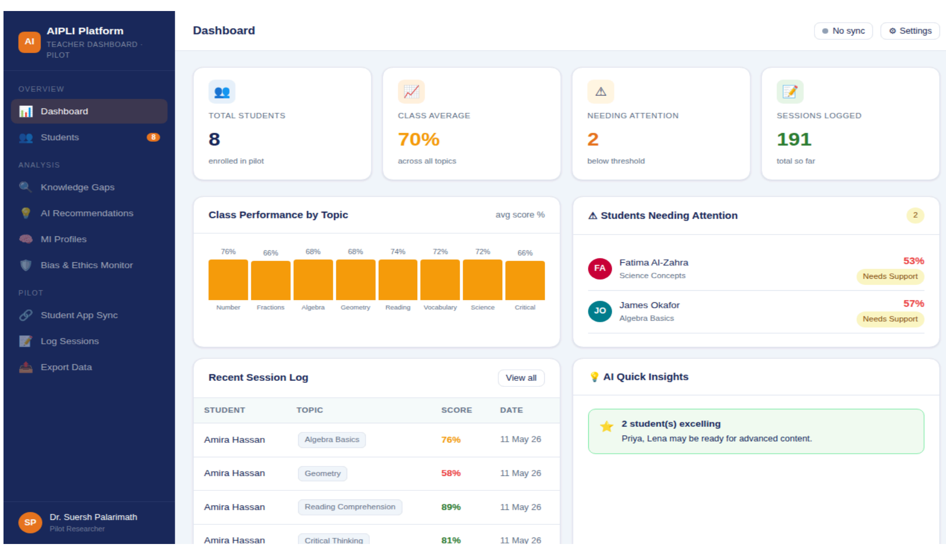

Figure 1. Educator Cockpit: class performance heatmap, at-risk identification, AI Quick Insights, and MI Profiles tab (191 sessions, 8 students, 70% class average)

Development Methodology. DSRM [5] structured development across four phases: PRISMA-guided systematic review (247 papers); framework design informed by the problem space characterization in [2];

expert Delphi validation and benchmark simulation; and full platform implementation with pilot evaluation. The quantitative stakeholder evidence reported in [4] further informed the framework design priorities, confirming practitioner demand for transparency and equity-aware AI in assessment.

Platform Architecture. AIPLI Hub comprises eight integrated browser-based modules: AIPLI Central (launchpad), Educator Cockpit (teacher analytics), three adaptive student apps (Science Explorer, Math Navigator, Word Voyager), Intelligence Compass (MI assessment), Learning Path Engine (BKT dashboard), and Dataset Analyzer. Figure 1 shows the Educator Cockpit, which tracked 8 pilot students across 191 sessions.

BKT Engine. The Learning Path Engine (Figure 2) implements the Bayesian Knowledge Tracing model originally proposed by Corbett and Anderson (1994), with parameters validated by [8]. P(Learned) is updated after each response using:

$$P(L_n|correct) = P(L_{n-1})(1-P(S)) \;/\; [P(L_{n-1})(1-P(S)) + (1-P(L_{n-1}))\times P(G)]$$

$$P(L_n) = P(\hat{L}_n) + (1-P(\hat{L}_n)) \times P(T) \qquad [\text{Mastered: } P(L) \geq 0.95]$$

Composite recommendation scoring weights BKT knowledge need (45%), spaced repetition urgency (25%), ZPD difficulty fit (15%), and session confidence (15%). Parameters were calibrated against published benchmarks from [8] ($P(L_0)=0.24$, $P(T)=0.17$, $P(G)=0.21$, $P(S)=0.08$) and the EdNet dataset reported by Choi et al. [10] ($P(L_0)=0.30$, $P(T)=0.20$, $P(G)=0.25$, $P(S)=0.10$).

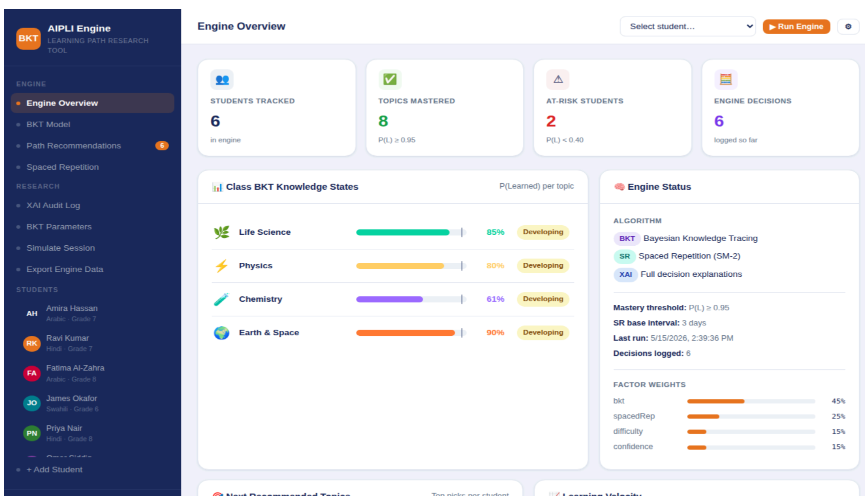

Figure 2. Learning Path Engine: BKT P per topic, XAI factor weight breakdown, and spaced repetition schedule

Validation. Two Delphi rounds with 15 experts (EdTech practitioners n=5, AI researchers n=5, policymakers n=5) achieved ≥80% consensus on all 12 core framework statements including BKT parameter validity (100%), MI-BKT integration benefit (87%), and XAI adequacy (93%). This validation approach builds on the stakeholder engagement methodology established in [4], extending quantitative perception analysis to framework design consensus. Simulation across four large-scale educational datasets-EdNet (121M+ interactions [10]), OULAD, ASSISTments [8], and Khan Academy-confirmed adaptive path consistency ≥90% and cross-dataset stability. BKT model evaluation yielded Accuracy=82.4%, Precision=83.5%, Recall=86.3%, F1=84.9%, and Specificity=77.4%, consistent with published benchmarks reported in [8]. Pilot equity audit confirmed performance gaps ≤8% across gender and language subgroups, satisfying the fairness requirements identified in the LMIC context review by [9].

4. Discussion

AIPLI Hub resolves all three structural exclusion deficits grounded in the authors' prior work [2][4]. The IndexedDB architecture eliminates server dependency, enabling full adaptive functionality on shared school computers and low-spec devices without connectivity — addressing infrastructure constraints documented by [9] and confirmed as a critical practitioner concern in [4]. The dual personalization dimension — BKT difficulty plus MI modality — operationalizes [7] argument that learning style awareness must complement knowledge state modelling for inclusive education, extending Gardner's theoretical framework [6] into a deployable system for the first time. The XAI factor-weight audit log addresses the algorithmic opacity problem highlighted in [3], enabling teachers to engage as informed collaborators rather than passive recipients of opaque AI decisions. Longitudinal MI tracking revealed a Kinesthetic-to-Spatial intelligence shift in one pilot student across two assessment cycles — consistent with developmental MI theory [7] and demonstrating a research capability unique to AIPLI Hub.

Conclusion

- 300 million+ LMIC learners excluded from adaptive EdTech due to server dependency, cognitive homogeneity, and algorithmic opacity — a problem space formally established and quantitatively validated across stakeholder groups.
- DSRM across four phases — literature synthesis (247 papers), Delphi validation (n=15, 2 rounds, ≥80% consensus), benchmark simulation (EdNet, ASSISTments, OULAD, Khan Academy), operational pilot deployment (8 students, 191 sessions).
- BKT path consistency ≥90%; F1-Score 84.9%; equity gap ≤8%; 70% pilot class average; first system integrating BKT + MI + XAI + offline IndexedDB in a deployable educational platform.
- Small pilot cohort (n=8); BKT parameters require AIPLI-specific empirical calibration beyond benchmarks; MI instrument requires psychometric validation; multilingual content (Arabic, Hindi, Swahili, French) needed per LMIC context analysis; large-scale RCT required for causal outcome evidence.

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