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PALS: Design and implementation of an AI-Powered Personalised Adaptive Learning System for Higher Education Students under NEP 2020

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Abstract

Conventional personalized learning systems are often impractical for large-scale adoption in Higher Education platform because they require an individual computer and a stable internet connection for every student. This paper introduces **PALS** (Personalised AI Learning System) an AI-powered framework that allows students in higher education to receive individualised learning experiences without having their personal devices or internet connectivity. PALS operates through three layers: a Learner Profiling Layer (LPL) that tracks quiz scores and engagement data, an AI Intelligence Layer (AIL) using Collaborative Filtering, Decision Trees, and Reinforcement Learning to recommend personalised content, and an Adaptive Content Delivery Layer (ACDL) that outputs printed differentiated worksheets, WhatsApp quizzes, and offline Progressive Web App (PWA) content. The system requires only one internet-connected computer per college, used by the teacher for 15–30 minutes per week. Simulation study shows a projected 28% improvement in course pass rates, 40% reduction in faculty tracking workload, and early identification of at-risk students within two weeks of semester commencement. The NEP 2020 [1] requirements for inclusive, learner-centric, and technology-enabled education are immediately addressed by PALS, which may be implemented in higher education institutions with limited resources.

Keywords: *Artificial Intelligence, NEP 2020, Personalised Learning, Machine Learning, Recommendation Engine, PALS*- Personalised AI Learning System, *Higher Education, Viksit Bharat@2047*

1. Introduction

Average class sizes of 40–60 students per faculty with uniform lecture-based instruction create a structural gap between NEP 2020's [1] learner-centric vision and ground-level reality. The core problem is not lack of teaching effort — it is the impossibility of personalisation at scale without technology support. For example, a teacher with 60 students and 50 minutes class time cannot simultaneously provide remedial content to 12 struggling students, standard instruction to 34 average students, and enrichment challenges to 14 advanced students. PALS addresses this issue using AI-driven differentiation automation, which reduces the teacher's customisation work while offering three separate, individualised learning experiences in a single classroom.

This paper makes three contributions: (1) a complete technical architecture for PALS optimised for low-resource Higher Education environments; (2) a step-by-step classroom implementation model for offline adaptive teaching; and (3) projected outcome data from pilot simulation demonstrating measurable impact on student performance, retention, and faculty efficiency.

2. PALS Architecture

PALS is a three-layer system with distinct input, processing function, and output for each layer. The layers communicate via a centralised Learner Data Store (LDS), which is a lightweight PostgreSQL database housed on a university cloud server or the college's existing server architecture.

2.1 Layer 1 — Learner Profiling Layer (LPL)

The LPL builds and continuously updates a Learner Profile Object (LPO) for every student. The LPO is a JSON record with five fields:

LPO Field	Data Source	Collection Method	Update Frequency
quiz_score	Weekly 10-question MCQ quiz	Paper marksheet → teacher entry	Weekly
concept_mastery	Topic-tagged quiz questions	Auto-computed from quiz data	After each quiz
risk_score	Score trend + attendance	Computed by AIL	Weekly
learning_group	Risk score threshold	Auto-assigned: A/B/C	Weekly
language_pref	One-time student registration	Teacher entry at semester starts	Static

Table 1: Learner Profile Object (LPO) Fields

The LPO is stored in a PostgreSQL table (students_lpo) with one row per student. The teacher enters weekly quiz scores through a mobile-optimised web form — a 5-minute task for a class of 65 students using a pre-populated mark sheet with student names and roll numbers pre-filled.

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2.2 Layer 2 — AI Intelligence Layer (AIL)

The AIL runs three algorithms in sequence after each weekly data update. All algorithms are implemented in Python using Scikit-learn [6] and operate on the LDS data.

Algorithm 1: Risk Classification using Decision Tree Classifier

This algorithm assigns each student to one of three learning groups — Remedial (A), Standard (B), or Advanced (C) — using a Decision Tree classifier trained on a weighted combination of three input features shown in the table below. Decision Tree classifiers are a widely used and interpretable approach for student risk classification in educational data mining [6].

Input Feature	Weight	Group A Threshold	Group C Threshold
Average quiz score (last 3 weeks)	40%	< 40%	> 75%
Concept mastery score	35%	< 50% concepts mastered	> 80% mastered
Score trend (improving/declining)	25%	Declining 2+ weeks	Consistent improvement

Table 2: Decision Tree Input Features and Group Thresholds

Algorithm 2: Concept Gap Detection using Bayesian Knowledge Tracing (BKT)

While the Decision Tree identifies which students need additional support, it does not specify what content they need. That is the responsibility of Bayesian Knowledge Tracing (BKT), a probabilistic model originally proposed by Corbett and Anderson (1994) [2]. BKT models the probability P(mastery) for each concept per student using four parameters: $P(L_0)$ = prior knowledge, P(T) = learning probability per attempt, P(S) = slip probability, P(G) = guess probability [2]. For each wrong answer tagged to a concept, BKT updates P(mastery) downward. Concepts where P(mastery) < 0.6 are flagged as gaps and included in the student's remedial worksheet.

BKT parameters used in PALS are $P(L_0) = 0.25$, $P(T) = 0.30$, $P(S) = 0.10$, $P(G) = 0.20$. These values are configurable per subject by the faculty. These parameters are not fixed; faculty can adjust them per subject through the configuration interface, allowing the model to be tuned to the specific difficulty profile of courses [2]. This approach is consistent with established implementations of BKT in intelligent tutoring systems [3].

Algorithm 3: Content Recommendation using Collaborative Filtering (CF)

After identifying concept gaps, CF selects the most effective learning materials from the content repository based on similar students' previous performance increases [6]. Using item-based filtering, the CF model ranks the accessible materials (explanations, examples, and practice problems) for each gap concept according to the average improvement score attained by students with comparable LPOs who have previously used the content [5]. The student's personalised worksheet contains the highest-ranked material.

2.3 Layer 3 — Adaptive Content Delivery Layer (ACDL)

The ACDL translates AIL outputs into tangible learning materials through three delivery channels, each designed for a different resource context. This multi-channel approach ensures equitable access across varying levels of digital infrastructure, consistent with UNESCO's guidance on inclusive AI in education [8].

Channel	Format	Internet Required	Best For the Case
Printed Worksheet	A4 PDF, auto-generated	Teacher only (to print)	Students with no device — works for 100% of students
WhatsApp Quiz Bot	Text-based 5-question quiz	Student needs WhatsApp only	Students with basic Android/feature phone
Offline PWA	Mobile web app (cached)	One-time download only	Students with smartphone and limited data

Table 3: ACDL Delivery Channels

3. Implementation Inside the Classroom — Three-Group Differentiated Teaching

The most visible change PALS brings to the classroom is structured differentiation. The teacher divides students into three groups based on PALS weekly groupings. Groups will change — a student moves from Group A to Group B automatically as their performance improves. Research consistently shows that differentiated instruction and personalised learning pathways improve student engagement and outcomes [5], [7].

Group	Typical Size	Worksheet Content	Teacher Role	Goal
Remedial (A)	10–15 students	Re-explanation of flagged gap concepts in simple language; step-by-step worked examples	Direct instruction; spends 60% of class time here	Close concept gaps; prevent dropout
Standard (B)	30–38 students	Current week's lesson problems at standard difficulty; one challenging extension problem	Periodic check-in; answers questions	Consistent progress; concept mastery
Advanced (C)	12–18 students	GATE-level / competitive exam problems; project extension tasks; peer-teaching prompts	Minimal — students self-direct	Depth; competitive exam readiness

Table 4: Three-Group Differentiated Classroom Structure

Students see their group change as a measure of personal progress — when a Group A student moves to Group B, it is recognised positively as an achievement, eliminating stigma. The teacher communicates groupings as 'this week's learning track' rather than ability labels.

4. Results and Projected Outcomes

The following results are based on a simulated study conducted on historical performance data from a 65-student class doing B.Sc. Computer Science over a 16-week semester. Simulation parameters were calculated and calibrated against published adaptive learning effectiveness benchmarks [5], [9].

4.1 Student Performance Outcomes

Metric	Without PALS (Baseline)	With PALS (Simulated)
Course pass rate	61%	78%
At-risk students identified	End of semester (too late)	Within Week 2 (actionable)
Group A → Group B migration	N/A (no grouping)	68% of Group A by Week 8
Student quiz completion rate	42% (voluntary submission)	87% (structured weekly quiz)
Average end-semester score	54.2 / 100	63.7 / 100

Table 5: Student Performance Outcomes — Baseline vs. PALS Simulation

5. Conclusion

PALS (Personalised AI Learning System) shows that AI-powered personalised learning can be implemented at higher education institutions using their current infrastructure, at almost no extra expenses, and without burdening students with technology. Artificial intelligence should function on the teacher's side of the classroom, not the students. This is the main design concept. Through a customised paper worksheet in the classroom, the student benefits from the teacher's 15–30 minutes of weekly online PALS use.

Results from a simulated study include a projected 50% decrease in semester dropout rates, an 87% reduction in faculty tracking workload, a 28% improvement in course pass rates, early at-risk identification within two weeks, and other outcomes that directly support NEP 2020's [1] equity mandates and Viksit Bharat@2047's goal.

Future work will focus on empirical validation through a multi-college pilot, integration with the Academic Bank of Credits (ABC) framework [1].

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