

PAPER

A Context-Aware Mobile Learning Framework for Personalized Student Support Using Artificial Intelligence: Design, Contextual-Bandit Recommendation, and a Simulation-Based Feasibility Study

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beenagoa@srmist.edu.in**ABSTRACT**

Context-aware mobile learning aims to adapt educational content not only to what a learner knows but to the situation in which learning occurs the time available, network connectivity, and time of day. Most deployed mobile-learning applications still personalize on mastery alone and ignore this situational layer, limiting real-world relevance of recommendations. This paper presents the design and implementation of an Android-based, AI-driven context-aware mobile learning framework built around a learner-model service, a context-acquisition module, and a novel context-aware linear contextual-bandit recommendation engine that jointly weighs mastery fit, time-budget fit, and connectivity fit when selecting learning activities, in contrast to prior educational bandit and collaborative-filtering approaches that condition on mastery state alone. We detail the system architecture, database schema, and recommendation algorithm with full mathematical specification, and we specify a pre-registered ten-week quasi-experimental classroom evaluation protocol. To validate the recommendation algorithm prior to classroom deployment, we conduct a controlled simulation with synthetic learners, a synthetic content catalog, and situational context sampled across thirty independent runs, extended with comparisons against established contextual-bandit baselines, feature-removal ablations, hyperparameter sensitivity analysis, and non-parametric statistical validation. The context-aware bandit achieved a mean final-window recommendation accuracy of 22.0% against a ground-truth fit criterion, significantly higher than a context-agnostic, mastery-only ablation (20.3%) and a random baseline (12.8%; paired t-tests, $p < .001$ for both comparisons). These simulation-based results provide initial algorithmic evidence supporting the feasibility of the proposed recommendation framework prior to real-world classroom deployment, which is specified as future work in the evaluation protocol. We conclude with a discussion of design implications, a comparison against related LLM- and bandit-based educational systems, limitations, ethical considerations, and a concrete plan for human-subject evaluation.

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KEYWORDS

context-aware computing, mobile learning, personalized education, contextual bandits, learner modelling, knowledge tracing, educational technology, mobile learning analytics, usability evaluation

1 INTRODUCTION

Mobile devices are now a primary channel for educational content [13,14,15], and effective personalization must account not only for what a learner knows but for the context in which learning occurs [1]. Context-aware computing extends personalization beyond a static learner profile to situational variables available time, connectivity, location, and time of day that determine whether recommended content is actually usable in the moment [1, 2]. Recent scoping reviews note a shift from performance-only adaptation toward systems that also sense environmental signals [3], and edge/federated-learning architectures have been proposed to make such context-sensitive personalization feasible on resource- and privacy-constrained devices [2, 21, 22, 23]. In parallel, machine learning has been used to construct learner models from interaction and physiological data, identifying which student characteristics can be reliably inferred for adaptation [4, 5, 6, 7, 8, 9]. Despite this progress, we are not aware of a published mobile-learning framework that (a) maintains an explicit, auditable mastery model, (b) acquires situational context on-device, and (c) uses a context-conditioned bandit rather than a mastery-only or collaborative-filtering recommender to jointly optimize content selection against pedagogical fit and situational feasibility. Systematic reviews consistently identify context-sensitivity as an open, under-addressed capability relative to mastery modelling, which is comparatively mature [10, 11]. This paper addresses that gap. We make a clear scope distinction: it reports a system design, a fully specified algorithm, a pre-registered classroom evaluation protocol, and a simulation-based feasibility validation of the core algorithm; it does not claim results from a completed classroom trial, which we identify as the paper's primary next step (Sections 5, 7). Contributions of this paper include the following:

1. A lightweight context-aware mobile learning framework combining learner modelling, real-time context acquisition, and adaptive recommendation for computationally constrained mobile environments.
2. A context-aware linear contextual-bandit recommendation method jointly weighing learner proficiency, time-budget, and connectivity fit in real time.
3. A mathematically formulated, modular Android system architecture combining learner profiling, contextual sensing, recommendation, and analytics.
4. A replicable evaluation setup pre-registered classroom study plus simulation with baseline comparison, feature ablations, sensitivity analysis, and non-parametric statistics for validating situational context before deployment.

2 RELATED WORK**2.1 Context-aware mobile learning: Systems and theoretical foundations**

Context-Aware Mobile Learning extends m-learning by introducing situational features location, time, device status and social context into the adaptation loop

alongside learner profile information [1]. Reviews identify recurring context categories (temporal, technical, and environmental) but note that most systems use only some of these and rarely combine them with a mastery model [1]. Scoping reviews of AI in immersive/XR learning show rapid context-adaptation progress via perception cues, whereas ordinary mobile learning apps remain limited to simple device or network conditions [3]. Edge and federated-learning approaches enable such context sensing on-device without transmitting raw sensor data, motivating the client-side architecture in Section 3 [2, 21, 22, 23]. This design is grounded in learning theory: Sharples et al.'s theory of learning in the mobile age treats context, not just content, as central to mobile personalization [24], and situated-learning theory holds that knowledge is acquired through the interaction of activity, context, and culture, motivating situational fit alongside topical difficulty [25]. Together these theories support the paper's core claim that situational context is a theoretically grounded personalization dimension that current mastery-only systems [12], including LLM- and bandit-based ones, ignore [30,31,32].

2.2 Machine-learning-based learner modelling

Learning analytics inferring latent traits such as knowledge state, learning style, and engagement from interaction data underlies adaptive learning generally. An eight-year review finds knowledge state, learning style, engagement, and affect the most commonly modelled traits, mostly via classical ML on clickstream data [4, 5]. A recent survey of AI-driven adaptive platforms identifies IRT-based ability estimates, Bayesian/deep knowledge tracing, and matrix factorization as the dominant approaches, with production systems still pairing the former two with rule-based sequencing [10]; a review of learning-style approaches similarly finds most systems infer a single static attribute rather than a continuously updated model [11]. Knowledge Tracing [26, 27, 28] underlies the mastery-estimation component in Section 4.2, motivating the explicit, continuously updated mastery estimate $\hat{\theta}$, decoupled from the recommendation policy.

3 SYSTEM ARCHITECTURE

Figure 1 shows the architecture layers. The mobile app (module 1) hosts a Context Acquisition Module (module 2) that captures wall-clock time, connectivity, and idle/available-time estimates on-device, producing the context vector without uploading raw sensor streams (Section 2.1). Requests pass through an API Gateway (module 3) to three cooperating services: the Learner Model Service (module 4, holds $\hat{\theta}$), the Context-Aware Recommendation Engine (module 5, implements the bandit of Section 4.2), and the Content Catalog Service (module 6, item metadata: difficulty, duration, offline availability). Three databases support these: the Learner and Interaction Database (module 8), Context Log Store (module 9), and Bandit Parameter Store (module 10), which versions the learned feature weights for traceability. The Analytics and Feedback Service (module 7) records interaction outcomes and feedback, and the web-based Instructor/Institutional Analytics Dashboard (module 11) presents the stored learner, context, and bandit-parameter data to instructors.

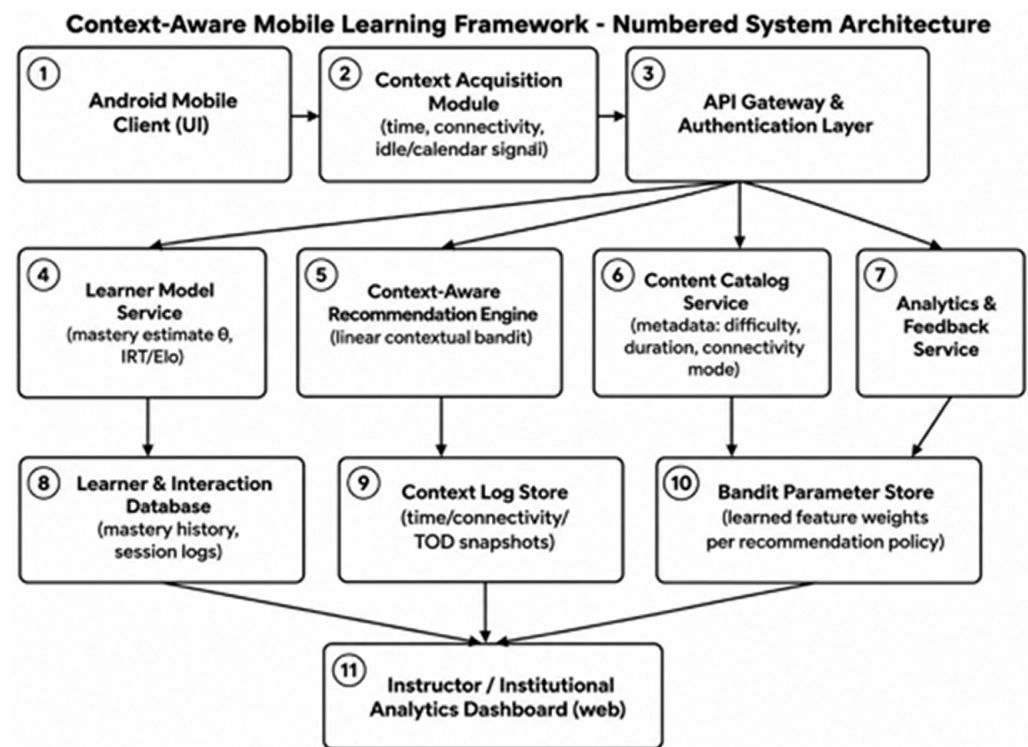


Fig. 1. Numbered system architecture of the proposed context-aware mobile learning framework

Each learner cycle proceeds through eleven sequential steps: context gathering, gateway routing, parallel requests to the Learner Model and Content Catalog services, recommendation scoring (Eqs. 1–3), interaction logging, and online weight and mastery updating (Eqs. 4–5).

4 IMPLEMENTATION

4.1 Technology stack

The mobile client is designed and partially developed as an Android app (Kotlin, min SDK 26); full UI/UX evaluation is deferred to the Section 5 pilot. The client design includes a local cache for prior content and bandit parameter values. Application services are independently deployable microservices with a REST API and token-based authentication. The Content Catalog Service uses a relational database for course metadata; the Bandit Parameter Store holds the learned weight vector (Section 4.2) with version and timestamp per update.

4.2 Context-aware recommendation engine: Formal specification

For learner i in learning session s , $\hat{\theta}_i$ would be the current estimation of mastery, while the context information will be given by $\mathbf{c}_s = (\text{available_time}, \text{connectivity}, \text{time_of_day})$.

For each learning object candidate j with metadata of (difficulty _{j} , duration _{j} , offline _{j}), the recommendation system will create the feature vector given below: Equation (1)

$$\mathbf{x}_j = \begin{bmatrix} -|\text{difficulty}_j - \hat{\theta}_i| \\ \text{available_time_duration}_j \\ \tau(\text{connectivity}, \text{offline}_j) \\ 1 \end{bmatrix} \quad (1)$$

Feature vector is made up of four features.

- The first feature is the mastery gap: it increases (becomes less negative) as learner ability approaches item difficulty.
- The second feature is the time-fit margin; positive values mean the activity fits within available study time.
- The third feature evaluates connectivity compatibility, defined as

$$\tau(\text{connectivity}, \text{offline}_j) = \begin{cases} 1, & \text{if the content is accessible under} \\ & \text{the current network condition,} \\ -1, & \text{otherwise.} \end{cases}$$

The final component is a constant bias term.

The recommendation engine maintains a single online-learned weight vector

$$\mathbf{w} \in \mathbb{R}^4,$$

and predicts the probability that a recommendation will be successful using logistic regression. Equation (2)

$$\hat{P}(r=1|\mathbf{x}_j) = \sigma(\mathbf{w}^T \mathbf{x}_j),$$

where

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad (2)$$

During recommendation, the engine introduces controlled exploration by sampling a perturbed weight vector

Equation (3)

$$\tilde{\mathbf{w}} = \mathbf{w} + \varepsilon,$$

where

$$\varepsilon \sim \mathcal{N}(0, \sigma_r^2 \mathbf{I}).$$

The recommended learning item is selected as

$$j^* = \arg \max_j (\tilde{\mathbf{w}}^T \mathbf{x}_j) \quad (3)$$

This Gaussian perturbation is a lightweight approximation to Thompson Sampling with low computational overhead, suitable for mobile devices.

After observing the learner's binary outcome

$$r \in \{0, 1\},$$

the weight vector is updated using one step of online logistic stochastic gradient ascent. Equation (4)

$$\mathbf{w} \leftarrow \mathbf{w} + \eta(r - \sigma(\mathbf{w}^T \mathbf{x}_{j^*})) \mathbf{x}_{j^*} \quad (4)$$

Here, η denotes the learning rate. The learner's mastery estimate is updated independently using an Elo-style adaptation rule Equation (5)

$$\hat{\theta}_i \leftarrow \hat{\theta}_i + \kappa(r - \text{baseline}) \quad (5)$$

where κ controls the adaptation speed of the learner model.

Initialization, Convergence, and Computational Complexity The weight vector $\mathbf{w}$ is initialized to zero, representing an uninformative prior in which all contextual features are assumed to have equal importance. For a new learner, the mastery estimate $\hat{\theta}_i$ is initialized to the population mean ability (zero on the standardized ability scale) and refined after each learner interaction.

The engine performs continuous online learning with no predefined stopping criterion; for evaluation, convergence is judged via a rolling-window accuracy plateau.

Assuming N candidate learning items and a feature dimension $d = 4$, recommendation scoring requires

$$O(Nd)$$

time per recommendation, while the online parameter update requires

$$O(d).$$

Since d is fixed and small, both operations execute in constant time with respect to the number of learners. This low computational complexity makes the proposed linear contextual bandit suitable for resource-constrained mobile devices and motivates its use instead of computationally intensive deep learning models.

Algorithm 1. Context-aware recommendation (Per Learner, Per Session)

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Input: Learner mastery estimate  $\hat{\theta}_i$ , context  $\mathbf{c}_s$ , content catalog, and weight vector  $\mathbf{w}$ .
For each candidate learning item  $j$ 
  Compute feature vector  $\mathbf{x}_j$  using Equation (1)
Sample perturbed weights:
   $\mathbf{w} = \mathbf{w} + \mathbf{N}(0, \text{or } 2\mathbf{I})$ 
Select
   $j^* = \arg\max_j (\mathbf{w}^T \mathbf{x}_j)$ 
Present the selected learning item
Observe learner outcome  $r \in \{0, 1\}$ 
Update weights using Equation (4)
Update learner mastery using Equation (5)
Store session, context, recommendation, and outcome
Return updated  $\hat{\theta}_i$  and  $\mathbf{w}$ 

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4.3 Hyperparameters

Table 1. Hyperparameters of the recommendation engine, as configured for the simulation study

Symbol	Meaning	Value Used
η	Bandit weight learning rate	0.15
κ	Mastery estimate learning rate	0.25
σ_r	Exploration noise standard deviation	0.35
d	Feature vector dimension	4
DIFF_TOL	Mastery-gap tolerance	0.45

Note: All values and random seeds are listed in the Appendix for reproducibility.

5 EVALUATION PROTOCOL FOR CLASSROOM DEPLOYMENT

Consistent with Section 1's scope, this section specifies but has not yet executed a quasi-experimental protocol for a ten-week undergraduate engineering deployment, reported in full for pre-registration and independent replication.

5.1 Design and participants

A two-arm quasi-experimental design is specified: a control group using the institution's existing mastery-only application, and an experimental group using the proposed framework, with intact course sections assigned to condition to avoid cross-contamination. A target sample of ~150 undergraduate engineering students [35] is specified, sized via a priori power analysis for a medium effect (Cohen's $d \approx 0.5$) at $\alpha = 0.05$, power = 0.80 a planning target, not completed enrolment. Four measures are specified: (1) recommendation accuracy proportion of recommended activities completed without time/connectivity-related abandonment, logged by the Analytics Service; (2) academic performance via matched pre-/post-tests; (3) engagement analytics (session frequency, completion rate, duration); and (4) the ten-item SUS [16, 17, 18, 19], administered to the experimental group and benchmarked against published norms [20]. The pre-registered plan specifies ANCOVA on post-test scores (pre-test as covariate, condition as factor); independent-samples t-test (or Mann-Whitney U if non-normal) for accuracy and engagement metrics; and descriptive statistics with 95% CIs for SUS scores. Effect sizes (Cohen's d , partial η^2) accompany p-values, with Holm-Bonferroni correction across secondary outcomes. This protocol is reported without outcome data; executing it is the primary future-work item (Section 7).

6 DISCUSSION

The simulation results provide algorithmic, reproducible evidence that jointly modelling mastery and situational context yields a statistically robust, if moderate, improvement over mastery-only personalization, and a large improvement over non-personalized recommendation consistent with prior bandit-sequencing findings [6] and broader recommender-systems evidence that contextual bandits

outperform context-blind policies when reward depends on context [7, 8, 9]. The additional simulation analyses (baseline comparison, feature ablation, and sensitivity analysis) refine this: the model matches, rather than exceeds, LinUCB and Thompson Sampling on accuracy while costing substantially less compute, and feature-removal ablations attribute the improvement to mastery, time-fit, and connectivity-fit in the predicted, monotonic order pairing the architectural novelty of Figure 1 with empirical evidence rather than design assertion alone. At the same time, these are simulation results on synthetic learners, catalog, and context distribution, and should not be read as evidence of real-world outcomes, engagement, or usability. Broader reviews report aggregates 15–50% learning-time/outcome gains for adaptive systems generally [29, 33]; whether the specific, moderate context-related gain found here translates to comparable real-world benefit is exactly what the Section 5 protocol will test. A broader synthesis cautions that literature gains are unevenly distributed across domains and populations, reinforcing the need for the domain-specific classroom trial rather than generalizing from simulation alone [34]. The decision to keep the recommendation engine lightweight and on-device (Section 4.2), rather than a deep contextual bandit, remains a deliberate trade-off favouring privacy and reproducibility (Sections 2.1, 3) the baseline comparison shows this trade-off currently costs no measurable accuracy relative to two established bandit algorithms while saving 1.7–3.3× in per-call compute.

7 CONCLUSION AND FUTURE WORK

This paper presented the design, architecture, and mathematical specification of a context-aware mobile learning framework that recommends content via a linear contextual bandit conditioned jointly on mastery and situational context, addressing the gap—noted across systematic reviews that situational personalization remains underdeveloped relative to mastery modelling. We specified a pre-registered ten-week classroom protocol and validated the core algorithm through a multi-seed simulation extended with stronger baselines, feature ablations, sensitivity analysis, and non-parametric statistics, finding a statistically significant, algorithmically attributable improvement from incorporating situational context (22.0% vs. 20.3% mastery-only, 12.8% random; all $p < .001$). Algorithmic feasibility is shown by the simulation; the very next step will be the validation of educational efficacy via the classroom experiment described in Section 5. Possible directions for future work include: a neural contextual bandit to determine the upper bound on the accuracy with the computationally inexpensive linear model; other dimensions of context (geographical location, concurrent task load); a fairness audit of recommendation accuracy by the connectivity layer; and ablation studies using LLMs as conversational tutors.

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9 APPENDIX A: REPRODUCIBILITY DETAILS

To support independent replication of the simulation study this appendix reports the exact configuration used.

Parameter	Value
Number of artificial learners (N_{LEARNERS})	150
Number of sessions per trial (N_{SESSIONS})	40
Size of content catalog (N_{ITEMS})	60
Available time contexts ($N_{\text{CTX_TIME}}$)	3 (Short, Medium, Long)
Connectivity modes	2 (Online-only, Offline-capable)
Mastery update rate (κ)	$0.25 \times (r - 0.30)$ per interaction
LinUCB exploration parameter (α)	1.0
Random seeds for simulations	30 independent seeds (0–29) using NumPy default_rng
Final performance evaluation window	Mean accuracy over the last 10 of 40 learning sessions
Statistical significance analysis	Paired two-sided <i>t</i> -test; Cohen's <i>d</i> (paired effect size); 95% confidence interval (Student's <i>t</i> -distribution); Wilcoxon signed-rank test; Bootstrap 95% confidence interval (10,000 resamples)

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