



STUDENT LEARNING USING AI

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Abstract

Artificial intelligence (AI) is increasingly being explored as a way to make digital learning more responsive to students' individual needs. This paper proposes an AI-assisted student learning system that combines learner preferences, topic-level progress, practice responses, and teacher feedback to recommend suitable learning resources and next-step activities. The proposed framework includes a learner interface, a content repository, a recommendation and feedback engine, progress analytics, and teacher oversight. Rather than treating a single score as a complete picture of ability, the system uses repeated learning evidence to identify topics that may need revision and to suggest practice at an appropriate level. The design emphasizes explainable recommendations, privacy, accessibility, and human supervision. A prototype could be developed using a web interface, a structured content store, and rulebased or machine-learning components selected according to available data. Evaluation should measure recommendation relevance, consistency, usability, learner engagement, and learning outcomes through a controlled and ethically approved study. No experimental performance is claimed in this conceptual paper; the framework and evaluation plan are presented for future implementation.

Keywords: Artificial Intelligence; Personalized Learning; Adaptive Learning; Educational Technology; Learning Analytics; Student Feedback; Human-Centred AI

2.1 PROBLEM STATEMENT

Learners often receive the same learning material despite differences in understanding and progress. Teachers may have limited time to identify every student's misconceptions and to prepare individualized practice. Some digital systems also provide recommendations without explaining why a resource was selected. The problem addressed here is the design of a transparent AI-assisted framework that uses learning activity evidence to guide students toward relevant resources while preserving teacher oversight and learner choice.

2.2 Objectives

- Design a learner profile that records only necessary preferences and learning progress.
- Recommend lessons and practice activities using topic mastery, learner goals, and content metadata.
- Provide actionable formative feedback rather than relying only on final scores.
- Create dashboards that help students and teachers review progress over time.
- Define a practical evaluation plan covering recommendation quality, usability, fairness, privacy, and learning outcomes.

2.3 Scope

The proposed prototype is intended for school or introductory college-level learning modules. It can initially focus on a small set of topics with teacher-reviewed content and quizzes. The framework does not diagnose learning disabilities, replace teachers, or guarantee improved academic performance. Recommendations should remain advisory and should not be used alone for high-stakes grading, admissions, or disciplinary decisions.

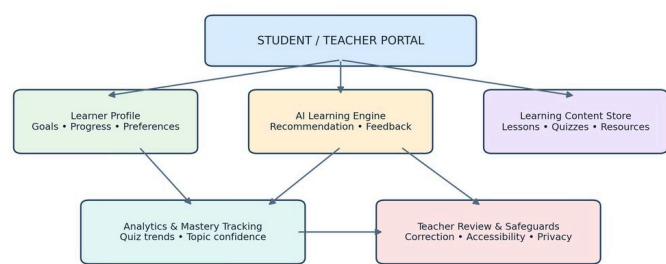
3. BACKGROUND AND RELATED WORK

Table 1. Learning Support Needs and Proposed Response

Learning need	Proposed system response	Human safeguard
Unclear next step	Suggest a lesson or practice set linked to the topic	Student can choose another option
Repeated mistakes	Show hints and targeted revision	Teacher can inspect the misconception
Progress hard to track	Display topic-level progress over time	Avoid unsupported ability labels
Different needs	Offer text alternatives and adjustable pace	Teacher reviews accessibility

4. PROPOSED SYSTEM ARCHITECTURE

The system is organized as a set of connected modules. The learner portal collects goals and activity responses. A content repository stores teacher-approved lessons, examples, quizzes, and metadata. The AI learning engine combines learner context with topic-level evidence to suggest resources and feedback. Analytics summarizes progress, while the teacher review module provides oversight and correction. Recommendations are updated after subsequent learning activity, creating a continuous improvement loop.



Personalized pathway is updated from learning evidence; teachers retain oversight.

Figure 1. Modular architecture for an AI-assisted learning system.

4.1 MAIN MODULES

TABLE II

Module	Input	Output
Learner portal	Goals, preferences, quiz responses	Learner activity and requests
Content repository	Approved lessons, quizzes, topic tags	Relevant learning resources
AI learning engine	Profile, performance history, content metadata	Ranked resources and feedback
Progress analytics	Attempts, completion, topic-level evidence	Progress summaries and trends
Teacher review	Recommendations and student context	Corrections, overrides, support actions

4.2 DATA FLOW AND INTERFACES

A typical request begins when a learner selects a topic or opens a recommended activity. The application retrieves relevant content and recent progress, applies recommendation logic, and returns a short list of resources with reasons. After the learner completes an activity, the response is stored and the topic profile is updated. Teachers should be able to view the reason for a recommendation and correct content or rules when necessary. Access controls must ensure that learners can view their own records and teachers can access only authorized student information.

4.3 EXPLAINABILITY BY DESIGN

Each recommendation should include a brief explanation, such as “Practice fractions because two recent exercises showed difficulty with equivalent fractions.” The explanation should be based on recorded evidence, not on a broad judgement about the learner. When evidence is limited or conflicting, the system should offer a diagnostic activity or ask the student to select a preferred path rather than presenting a confident but unsupported recommendation.

5. RECOMMENDATION WORKFLOW AND LEARNING CYCLE

The workflow combines learner input, learning evidence, recommendation logic, and feedback. It should be simple enough for students to understand and predictable enough for teachers to audit. The following flowchart illustrates the proposed cycle.

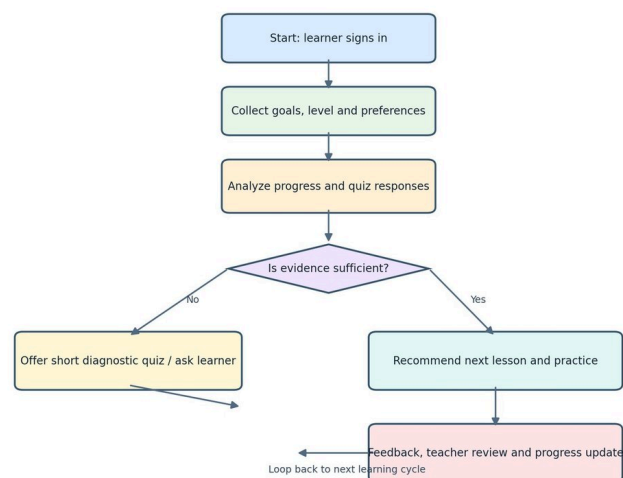


Figure 2. Decision flow for selecting an appropriate next learning activity.

5.1 RECOMMENDATION LOGIC

An initial prototype can use transparent rules before introducing a more complex model. For example: (1) if a learner repeatedly misses questions on a prerequisite concept, recommend a short revision lesson; (2) if performance is consistent across several attempts, offer a more challenging activity; (3) if evidence is insufficient, provide a diagnostic quiz; and (4) if a learner requests a different format, prioritize an available accessible alternative. These rules should be documented, tested, and reviewed by educators.

5.2 ILLUSTRATIVE RULE TABLE

TABLE III

Evidence pattern	Recommendation	Reason shown to learner
Repeated errors on same concept	Short explanation + guided practice	“Review this concept before moving ahead.”
Mixed or inconsistent responses	Diagnostic quiz with varied items	“A few more answers will help select practice.”
Consistent correct responses	Extension task or next topic	“Recent answers suggest you may be ready to progress.”
Learner requests visual support	Diagram, worked example, or video	“This format is available for the selected topic.”

5.3 FEEDBACK CHAIN

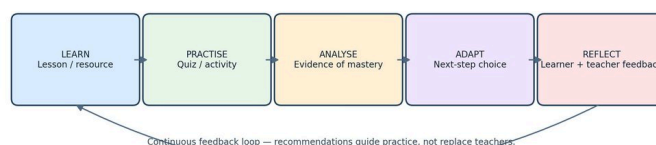


Figure 3. Learning chain linking practice, evidence, adaptation, and reflection.

6.1 DEVELOPMENT APPROACH

The project can follow an iterative design-and-evaluation process. First, a limited curriculum area is selected with teacher input. Second, learning objectives and resource metadata are prepared. Third, the learner interface and progress data model are implemented. Fourth, the recommendation engine is added using documented rules. Fifth, the prototype is tested with synthetic or consented pilot data before any broader use. Feedback from learners and teachers is used to refine explanations and navigation.

6.2 SUGGESTED TECHNOLOGY STACK

TABLE IV				
Layer	Possible tools		Purpose	
Web interface	Streamlit or React		Questionnaires, lesson views, dashboards	
Application logic	Python / FastAPI		Recommendation rules and APIs	
Data management	SQLite for prototype; PostgreSQL for deployment		Profiles, activity, content metadata	
Analytics	Pandas and Matplotlib		Progress summaries and evaluation charts	
AI component	Rule-based baseline;	validated ML/NLP if justified	Ranking, feedback assistance, content matching	

6.3 DATA MODEL

A practical data model may include Learner, LearningGoal, Topic, Resource, ActivityAttempt, Recommendation, Feedback, and TeacherReview records. A learner identifier should be pseudonymous where possible. Each activity attempt should record the topic, timestamp, response outcome, and relevant context needed for learning analysis. Sensitive information should not be collected unless a clear educational need and appropriate authorization exist.

6.4 RECOMMENDATION SCORE

Table 3. Example Candidate Resource Scoring Factors		
Factor	Example evidence	Design consideration
Topic relevance	Resource topic matches current goal	Avoid irrelevant suggestions
Prerequisite fit	Recent responses on prerequisite skills	Use multiple attempts, not one score
Format preference	Learner selects video or text	Offer alternatives when possible
Difficulty	Resource introductory/intermediate	tagged Allow learner and teacher override

7. EVALUATION PLAN

Evaluation should establish whether the system behaves as intended and whether students and teachers can use it effectively. Technical tests should precede any student pilot. If human participants are involved, the institution should approve the study process, provide age-appropriate information, obtain required consent or assent, and explain how data will be stored and used.

7.1 EVALUATION MEASURES

TABLE VI		
Measure	Method	Interpretation
Functional correctness	Predefined test cases for each recommendation rule	Checks whether expected behaviour occurs
Recommendation relevance	Educator rating of suggested resources	Assesses fit to topic and learning objective
Explanation clarity	Short learner/teacher questionnaire	Checks whether reasons are understandable
Usability	Task completion and user feedback	Identifies navigation and interaction issues
Learning outcome	Pre/post assessment in a suitable study design	Estimates change only with an appropriate comparison
Fairness and accessibility	Review across language, device, and access contexts	Identifies uneven experience or barriers

7.2 TESTING STRATEGY

• Unit tests: verify each rule using fixed input-output cases. • Integration tests: verify data moves correctly between interface, engine, and database. • Edge cases: test missing responses, conflicting signals, repeated attempts, and unavailable resources. • Content review: ask subject teachers to verify explanations, examples,

and difficulty tags. • Pilot study: document sample, procedure, measures, limitations, and analysis before reporting outcomes.

7.3 REPORTING RESULTS

Table 4. Risk and Mitigation Matrix			
Risk		Potential impact	Mitigation
Incorrect feedback	AI-generated	Learner receives misleading guidance	Use approved content, citations where relevant, and teacher review
Biased or incomplete data		Unequal recommendations	Audit across groups and allow manual correction
Privacy exposure		Unauthorized access to student records	Minimize data, apply access controls, define retention
Overreliance on recommendations		Reduced learner or teacher agency	Show explanations and preserve choice and override
Unequal connectivity or devices	Some learners cannot access features		Provide lightweight pages and offline alternatives

8.1 PRIVACY AND SECURITY

Student learning data can be sensitive even when it does not include medical or financial information. The prototype should collect only the minimum data needed for learning support, restrict access by role, protect data in transit and at rest, and define a retention and deletion policy. Identifiable student records should not be sent to external AI services without institutional approval and appropriate safeguards. Logs should avoid storing unnecessary personal text.

8.2 HUMAN OVERSIGHT AND TRANSPARENCY

AI-generated explanations may be incomplete or incorrect. The interface should identify automated suggestions, provide a way to report a problem, and make teacher review available for consequential decisions. Students should understand what evidence informs recommendations and how to request a different learning route. Consistent with UNESCO guidance, AI should support human agency and inclusive education rather than displace teacher judgement [1, 2].

8.3 ACCESSIBILITY AND INCLUSION

The design should use readable typography, keyboard-accessible controls, clear language, captions or transcripts for media, and mobile-friendly pages. Where feasible, resources should support multiple languages and low-bandwidth access. A learner's device, language, disability, or intermittent connectivity should not be treated as evidence of low ability. Accessibility testing should include the perspectives of students and educators who use different devices and learning formats.

9.1 EXPECTED OUTCOMES

The expected deliverable is a prototype that presents relevant learning resources, explains why they were recommended, records topic-level progress, and provides a teacher-facing review view. Supporting deliverables include a documented rule set, test cases, data model, risk checklist, and evaluation protocol. Whether these features improve learning or engagement must be determined by empirical evaluation. 9.2 Limitations The quality of recommendations depends on the accuracy of learning materials, resource tags, and the interpretation of activity evidence. Short quizzes may not capture deep understanding. Learner preferences can change, and performance can be influenced by context. If generative AI is used, outputs may contain errors or inappropriate examples. A small pilot may not generalize to different schools, languages, age groups, or curricula. The proposed system is therefore a support tool, not a substitute for teachers or professional educational assessment. 10. Conclusion This paper proposes an AI-assisted student learning framework that connects learner goals, topic-level evidence, adaptive recommendations, formative feedback, and teacher review. Its main design priorities are explainability, practical implementation, privacy, accessibility, and continued human oversight. A rule-based prototype offers a transparent starting point, while more advanced models should be introduced only when they provide a justified benefit and can be evaluated responsibly. Future work should implement the prototype, conduct technical testing, and carry out an ethically

approved usability and learning-outcome study before making claims about effectiveness.

TABLE VIII

Rule ID	Condition	Action
R1	Two or more recent errors on a prerequisite topic	Suggest revision and guided practice
R2	Insufficient recent evidence	Offer a short diagnostic activity
R3	Consistent mastery evidence and learner readiness	Offer extension activity
R4	Learner chooses an alternate format	Present an accessible equivalent if available

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[10] UNESCO, Recommendation on the Ethics of Artificial Intelligence. Paris: UNESCO, 2021. Available: <https://unesdoc.unesco.org/ark:/48223/pf0000381137>. Appendix A. Example Recommendation Rules Rule ID Condition Action R1 Two or more recent errors on a prerequisite topic Suggest revision and guided practice R2 Insufficient recent evidence Offer a short diagnostic activity R3 Consistent mastery evidence and learner readiness Offer extension activity R4 Learner chooses an alternate format Present an accessible equivalent if available Appendix B. Prototype Acceptance Checklist • Recommendation reasons are visible and understandable. • Learners can skip or change a recommended activity. • Teachers can review and correct content or recommendations. • Access permissions and data deletion procedures are tested. • Evaluation results are reported only after the relevant tests are completed.

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