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A Faculty-Centered AI-Based Personalized Learning Framework for Undergraduate and Postgraduate Students in Higher Education

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Abstract

Personalized learning is increasingly relevant in higher education because students entering the same course can differ in prior knowledge, topic-wise performance, learning pace, engagement, and preferred learning resources. A common instructional sequence may therefore provide insufficient support for some learners while offering unnecessary repetition to others. Artificial Intelligence (AI), Machine Learning (ML), and learning analytics can support a more responsive approach by identifying learner patterns and recommending resources or activities according to observed needs. This paper proposes a faculty-centered AI-based personalized learning framework for undergraduate (UG) and postgraduate (PG) students. The framework combines academic performance, assessment results, learning behaviour, resource preferences, and learner level to construct an evolving learner profile. A personalization engine uses this profile to recommend suitable learning resources, topic difficulty, practice activities, and learning sequences. A feedback loop updates recommendations after subsequent learning interactions and assessments. In addition, a faculty-support layer presents summarized information about weak topics, progress, and assessment trends so that instructors can provide targeted academic intervention. The paper defines the research gap, framework architecture, methodology, data requirements, evaluation plan, and ethical safeguards. No experimental results are claimed because implementation and empirical validation are proposed as subsequent research stages.

Keywords; Artificial Intelligence; Personalized Learning; Machine Learning; Adaptive Learning; Higher Education; Learning Analytics; Recommendation System; Faculty Support.

INTRODUCTION

Students in higher education do not begin a course with identical academic preparation. Within the same class, one learner may already be comfortable with a topic while another may require additional examples, guided practice, or revision of prerequisite concepts. Differences can also appear in assessment performance, learning pace, engagement with digital resources, and preferences for notes, videos, examples, or practice questions. A fixed instructional sequence makes it difficult for a faculty member to respond to all of these differences at the same time.

Personalized learning attempts to address this problem by adapting learning experiences to individual requirements. The growing use of Artificial Intelligence (AI), Machine Learning (ML), and learning analytics has created opportunities to identify patterns in learner data and use those patterns to support resource recommendation and adaptive learning pathways. Recent literature reviews indicate that AI-mediated personalization is an active research area in education, including higher education [1], [3], [4].

Existing work demonstrates that adaptive pathways can be implemented at university level. For example, Naseer et al. reported a deep-learning-based adaptive learning platform evaluated across four university courses with 300 students [2]. Such studies show the feasibility of moving from static digital content toward data-informed adaptation.

At the same time, the literature identifies continuing concerns related to privacy, teacher preparation, evaluation, explainability, and responsible use of learner data [1], [3].

The contribution proposed in this paper is therefore not the claim that AI-based personalization is new. Instead, the paper presents an integrated, faculty-centered framework that combines multiple learner characteristics, dynamically updates recommendations through feedback, and provides interpretable learner information for academic intervention. The framework is intended as a practical research design for UG and PG higher education rather than as a claim of completed experimental validation.

RELATED WORK

AI-based personalized learning has been investigated through adaptive learning systems, intelligent tutoring systems, learning analytics, recommendation systems, machine learning, deep learning, and more recently generative AI. Personalization can occur at several levels, including selection of content, recommendation of learning resources, adjustment of difficulty, feedback generation, assessment support, and construction of learning pathways.

Farhood et al. conducted a systematic literature review of AI-based personalized learning and classified applications around personalized content recommendations, personalized tutoring or support, and personalized feedback or assessment [1]. Their work highlights the breadth of AI applications while also identifying challenges that affect educational deployment.

Naseer et al. presented an empirical study of deep-learning techniques for personalized learning pathways in higher education [2]. Their work is relevant to the present proposal because it demonstrates that learner information can be used to move beyond a single learning sequence. The present framework differs in emphasis by treating personalization as a feedback-driven process involving both student-facing recommendations and faculty-facing academic support.

Merino-Campos reviewed higher-education studies and discussed the benefits of AI-driven adaptive learning alongside ethical, privacy, teacher-training, and evaluation challenges [3]. Bayly-Castaneda et al. reviewed 78 studies published between 2019 and 2024 and reported strong representation of higher education, with adaptive learning technologies prominent and growing interest in generative language models [4]. A further systematic review in Applied Sciences also reflects the continuing expansion of research on AI for personalized learning in higher education [5].

Taken together, these studies indicate that the technical feasibility of personalization is reasonably established, but there remains scope for research designs that integrate academic, behavioural, preference-based, and learner-level information while keeping faculty members involved in the decision process. This observation motivates the framework developed in the following sections.

RESEARCH PROBLEM AND GAP

The central research problem is the difficulty of providing individualized learning support to diverse UG and PG students within a conventional higher-education classroom. A common course structure may not adequately represent differences in prior knowledge, topic-wise performance, learning pace, engagement, or resource preference. Faculty members can identify some of these differences through classroom interaction and assessment, but manual monitoring becomes difficult as the number of students and learning activities increases.

The research gap addressed by this study is therefore an integration gap rather than an absence of AI research. Existing literature contains adaptive learning systems, recommendation approaches, and learning analytics, but there is scope for a practical framework that brings several learner dimensions together, updates recommendations as new evidence becomes available, and communicates actionable information to faculty members.

The proposed research consequently focuses on a feedback-driven architecture in which learner information is converted into a profile, the profile informs recommendations, and subsequent assessment or interaction data are returned to the profile. Faculty members remain responsible for academic decisions, while the AI component functions as decision support.

Integration Gap and Design Need

The gap is best understood as an integration problem across the learner-information lifecycle. Academic performance is often available in institutional systems, while topic-level quiz results, resource interactions, time-on-task, and preference information may exist in separate learning environments. A useful personalization framework must therefore define how heterogeneous evidence is transformed into a common learner representation before recommendations are generated.

A second part of the gap concerns temporal change. A learner profile based only on historical marks can become stale after a learner completes new practice or receives feedback. The proposed feedback loop addresses this issue by treating the profile as an evolving representation rather than a one-time classification. New assessment evidence is used to revise the next recommendation cycle.

A third part concerns the role of faculty. A technically accurate recommendation is not sufficient if instructors cannot interpret why it was generated or how it relates to classroom needs. The proposed faculty-support layer therefore acts as a human-in-the-loop interface. The framework deliberately avoids replacing academic judgement in high-stakes decisions.

RESEARCH OBJECTIVES

Research Questions

RQ1. Which academic, behavioural, and preference-related learner features are most useful for generating personalized learning recommendations?

RQ2. How can AI/ML techniques be used to construct useful learner profiles for UG and PG students?

RQ3. Does a feedback-driven personalization process improve the relevance of recommended learning resources compared with a static recommendation approach?

RQ4. How can AI-generated learner insights support faculty members in identifying topics or learners requiring academic intervention?

RQ5. Which measures provide a meaningful evaluation of learning improvement, engagement, recommendation relevance, and learner satisfaction?

PROPOSED AI-BASED PERSONALIZED LEARNING FRAMEWORK

The proposed framework is organized as a feedback-driven pipeline with six functional stages: learner data collection, data preprocessing, learner profiling, AI/ML-based personalization, learning interaction and assessment, and feedback-based profile updating. A separate faculty-support view communicates summarized information that can assist instructors.

Learner Data Layer. The framework may use previous academic scores, topic-wise quiz results, assignment performance, assessment attempts, time spent on learning resources, learning activity, resource preferences, and learner level (UG or PG). The principle of data minimization should be followed: only information required for the stated research purpose should be collected.

Data Preprocessing. Raw learner records can contain missing values, duplicate records, inconsistent formats, or attributes that do not contribute meaningfully to the research objective. Preprocessing should therefore include data cleaning, handling of missing values, removal of duplicates, normalization where appropriate, and feature selection based on relevance and data quality.

Learner Profiling. The profiling stage converts learner records into a representation of current learning needs. For example, a student may demonstrate strong performance in programming fundamentals but repeated difficulty with recursion. The profile should capture such topic-level differences rather than assigning a single label such as 'weak' or 'strong' to the entire learner.

AI/ML Personalization Engine. A baseline model can classify or cluster learner states depending on the available dataset and research question. Decision trees, random forests, or clustering methods may be considered at the baseline stage. Recommendation can initially use content-based rules and later be compared with hybrid or ML-based ranking approaches. The final algorithm should be selected after examining the collected data rather than assuming a particular model in advance.

Recommendation Layer. Based on the learner profile, the system may recommend introductory or advanced material, video resources, notes, worked examples, practice questions, quizzes, or a revised topic sequence. Recommendations should be linked to observable learner evidence so that both students and faculty can understand why a resource was suggested.

Feedback Loop. After a learner uses recommended resources and completes a quiz, assignment, or assessment, the new evidence is returned to the learner profile. The system can then increase or decrease the difficulty of subsequent material, recommend additional practice, or move the learner to the next topic. This makes the framework adaptive rather than static.

Faculty-Support Layer. Faculty members receive summarized information such as topic-wise weaknesses, progress trends, assessment performance, and learners who may benefit from additional support. The purpose is decision support. The system should not automatically make high-stakes decisions such as failing, grading, or denying learning opportunities.

Design Rationale

The framework is designed around five principles. First, personalization should be evidence-based: recommendations should be connected to observable learner information rather than opaque assumptions. Second, personalization should be topic-sensitive because a learner can be strong in one area and require support in another. Third, adaptation should be iterative so that the system can respond to changing performance. Fourth, faculty members should remain responsible for consequential academic decisions. Fifth, data collection should be limited to information necessary for the research purpose.

These principles distinguish the proposed framework from a static recommendation catalogue. A static system may associate a predefined learner category with a fixed set of resources. In contrast, the proposed architecture allows the same learner to receive different recommendations at different points in a course when new evidence changes the learner profile. The intended output is consequently a sequence of context-sensitive learning actions rather than a single recommendation.

Proposed Adaptation Logic

At each iteration, the system first identifies the current learner state from the available profile information. It then maps the state to candidate resources, practice activities, or topic sequences. After the learner interacts with the recommendation, assessment and interaction evidence are collected and returned to the profile. The next cycle can therefore preserve successful recommendations, increase support where performance remains weak, or reduce repetition where evidence indicates adequate mastery.

The adaptation logic is intentionally model-agnostic at the research-design stage. The source study proposes decision trees, random forests, clustering, content-based recommendation, and later hybrid or machine-learning ranking approaches as candidates. This avoids prematurely selecting an algorithm before the actual dataset, feature distributions, and research questions are known.

Table 1. Functional Components of The Proposed Framework

Component	Primary Function	Example Information / Output
Data Layer	Stores approved learner information	Scores, quiz results, activity, preferences
Processing Layer	Cleans and transforms records	Missing-value handling, feature selection
AI/ML Layer	Identifies learner patterns	Learner states, clusters, predictions
Personalization Layer	Generates learning recommendations	Resources, difficulty, practice, sequence
User Interaction Layer	Supports students and faculty	Recommendations, progress and weak-topic view

SYSTEM ARCHITECTURE AND WORKFLOW

The architecture contains five principal layers: Data Layer, Processing Layer, AI/ML Layer, Personalization Layer, and User Interaction Layer. The Data Layer stores approved learner information. The Processing Layer transforms raw records into usable features. The AI/ML Layer identifies learner patterns. The Personalization Layer maps those patterns to learning resources and activities. The User Interaction Layer presents recommendations to students and learner insights to faculty.

The operational flow is: Student Data → Data Preprocessing → Learner Profile → AI/ML Model → Personalization Engine → Recommended Learning Resources → Student Assessment → Performance Feedback → Updated Learner Profile. The cycle can repeat throughout a course so that recommendations reflect changing learner performance.

Figure 1 illustrates the proposed feedback-driven architecture.

Data-to-Decision Flow

The architecture can be interpreted as a sequence of controlled transformations. The Data Layer contains approved learner information. The Processing Layer converts raw records into consistent features. The AI/ML Layer identifies patterns or learner states. The Personalization Layer translates those states into learning actions. The User Interaction Layer presents recommendations and faculty-facing summaries. Assessment and interaction data then create the evidence required for the next iteration.

This separation is important for research evaluation because each layer can be examined independently. Data quality can be assessed before modelling; profiling can be compared across candidate algorithms; recommendation relevance can be evaluated separately from classification performance; and faculty usefulness can be studied through instructor feedback. The architecture therefore supports both system development and staged validation.

Faculty-Support Interaction

The faculty view is not simply an administrative dashboard. Its proposed purpose is to summarize evidence that may otherwise be difficult to monitor across a large class. Examples include repeated weakness in a particular topic, declining assessment performance, incomplete prerequisite activities, and groups of learners who may benefit from additional explanation or practice. The final academic response remains with the instructor.

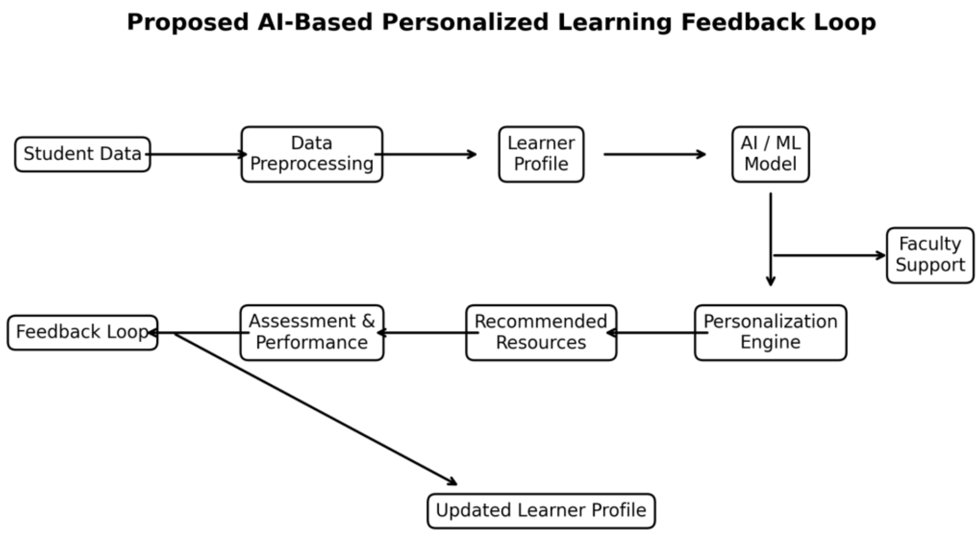

Figure 1. Proposed AI-based personalized learning feedback loop.

PROPOSED METHODOLOGY

Phase 1 – Literature Review. Recent peer-reviewed research on AI-based personalized learning, adaptive learning, learner profiling, recommendation systems, and higher education will be reviewed to establish the theoretical and technical basis of the study.

Phase 2 – Data Definition and Collection. A research dataset will be designed using variables such as learner level, previous academic performance, assessment scores, topic-wise performance, learning activity, time-on-task, resource preference, and interaction history. Data collection should begin only after the required institutional permissions, consent procedures, and data-protection safeguards are in place.

Phase 3 – Preprocessing and Feature Engineering. Missing values, duplicate records, inconsistent entries, and irrelevant attributes will be handled. Candidate features will be selected according to research relevance and data quality. Where appropriate, numerical variables can be normalized and categorical variables encoded.

Phase 4 – Learner Profiling. Baseline ML methods such as decision trees, random forests, or clustering can be evaluated. The choice should depend on the research question and the characteristics of the actual dataset. Topic-level performance should be retained where possible because aggregate marks can hide specific learning difficulties.

Phase 5 – Recommendation. A content-based recommendation mechanism can be implemented first because it provides a transparent baseline. A hybrid recommendation method or ML-based ranking model can subsequently be compared against the baseline.

Phase 6 – Feedback and Adaptation. After learners interact with recommended resources and complete assessments, their new evidence will be incorporated into the learner profile. The recommendation process will then generate the next set of learning resources or activities.

Phase 7 – Evaluation. If an approved experimental design is feasible, personalized and conventional learning conditions can be compared using pre-test/post-test learning gain, assessment performance, engagement indicators, recommendation relevance, and student satisfaction. Recommendation quality can additionally be examined through measures such as precision of relevant resource suggestions and learner acceptance of recommendations. No numerical outcome is reported in this paper because the empirical study has not yet been conducted.

Data Representation

The planned dataset should preserve the distinction between learner-level attributes and topic-level evidence. Candidate attributes include UG/PG level, previous academic performance, topic-wise quiz scores, assignment performance, assessment attempts, learning activity, time-on-task, resource preference, and interaction history. Topic-level representation is particularly important because aggregate marks may conceal localized learning difficulties.

Data preparation should also maintain temporal order where the research design requires it. A recommendation generated after an assessment should not use information that would only become available later. Preserving the sequence of interactions is therefore important for evaluating whether the feedback loop genuinely adapts to new evidence rather than indirectly using future information.

Baseline and Model Comparison Strategy

A transparent baseline is recommended before more complex approaches are introduced. Content-based recommendation can provide an interpretable reference point, while decision trees, random forests, or clustering can be evaluated for learner-state identification. A hybrid or machine-learning ranking approach can then be compared with the baseline if the dataset supports it. This staged strategy provides a clearer basis for attributing any improvement to the personalization mechanism.

Model selection should consider more than predictive performance. Interpretability, data requirements, computational complexity, stability across learner groups, and the ability to explain recommendations to faculty are also relevant. In an educational setting, a slightly less complex model may be preferable if its decisions are substantially easier to inspect and communicate.

Recommendation Generation

Candidate resources can be organized by topic, difficulty, prerequisite requirements, and resource type. The recommendation layer can then match learner evidence to suitable notes, videos, worked examples, practice questions, quizzes, or revised sequences. A recommendation should be accompanied internally by an evidence trace, such as repeated low performance on a topic or incomplete prerequisite activity, so that the reason for the recommendation can be inspected.

Feedback Update Procedure

After each learning interaction, the system records the new evidence and determines whether the learner state has changed. If performance improves, subsequent material can move toward the next topic or a higher difficulty level. If difficulty persists, the system can recommend additional explanation, worked examples, or practice. The important research object is the update mechanism itself: whether repeated cycles produce more relevant recommendations than a static approach.

Table 2. Research Methodology Phases

Phase	Core activity	Primary output
1	Literature review	Research basis and gap
2	Data definition and collection	Approved learner dataset design
3	Preprocessing and feature engineering	Usable, relevant features
4	Learner profiling	Topic-sensitive learner states
5	Recommendation	Transparent baseline recommendations
6	Feedback and adaptation	Updated learner profile
7	Evaluation	Learning and system-use evidence

EVALUATION FRAMEWORK

The evaluation should consider both educational outcomes and system usefulness. A multi-dimensional evaluation is preferable to relying only on prediction accuracy because the objective is improved learning support rather than classification performance alone.

Learning Performance: Pre-test and post-test scores, topic-wise quiz performance, assignment performance, and learning gain can be compared where the study design permits.

Engagement: Measures may include completion of recommended activities, time spent on resources, number of practice attempts, and continued interaction with the learning platform.

Recommendation Quality: The relevance and acceptance of recommended resources can be evaluated through learner feedback and recommendation metrics appropriate to the final system design.

Personalization Quality: The study can examine whether learners with different performance profiles receive meaningfully different resources, difficulty levels, or learning sequences.

Faculty Usefulness: Faculty members can evaluate whether the dashboard helps them identify weak topics, monitor progress, and decide where additional instructional intervention is needed.

Student Satisfaction: A structured questionnaire can assess perceived usefulness, ease of use, relevance of recommendations, and confidence in the personalized learning process.

Evaluation Design

The proposed evaluation should compare personalization as a learning-support process rather than as a classification exercise. Where institutional approval and an appropriate study design permit, learners receiving personalized recommendations can be compared with a conventional or static-recommendation condition. Pre-test and post-test measures can provide evidence of learning change, while interaction data can indicate whether recommendations were actually used.

Evaluation should also distinguish system-level and learner-level outcomes. System-level measures include recommendation relevance and faculty usefulness. Learner-level measures include learning gain, topic-wise performance, engagement, and satisfaction. This distinction reduces the risk of declaring the framework successful solely because a predictive model achieves high accuracy.

Recommendation and Personalization Measures

Recommendation quality can be examined through the relevance and acceptance of suggested resources and through metrics appropriate to the final recommendation implementation. Personalization quality can be examined by checking whether learners with different evidence profiles receive meaningfully different resources, difficulty levels, or sequences. A useful system should adapt when the learner state changes and should not produce nearly identical recommendations for substantially different needs.

Faculty Evaluation

Faculty evaluation should focus on actionability. Instructors can assess whether the system makes weak topics easier to identify, whether progress trends are understandable, whether recommendations provide sufficient evidence for review, and whether the dashboard supports timely intervention. This evaluation is aligned with the framework's faculty-centered contribution and preserves human oversight.

Table 3. Proposed Evaluation Dimensions

Dimension	Measures / evidence
Learning performance	Pre/post scores, topic-wise quizzes, assignments, learning gain
Engagement	Activity completion, time-on-task, practice attempts, continued interaction
Recommendation quality	Relevance, acceptance, appropriate recommendation metrics
Personalization quality	Differences in resources, difficulty, or sequences across learner profiles
Faculty usefulness	Weak-topic identification, progress monitoring, intervention support
Student satisfaction	Usefulness, ease of use, relevance, confidence

DATA PRIVACY, ETHICS, AND RESPONSIBLE AI

Student learning data are educational records and should be handled with appropriate institutional safeguards. Data collection should follow institutional approval and applicable consent requirements. Only the minimum information required for the research objective should be collected.

Where possible, identifiers should be removed or replaced with pseudonyms before analysis. Access to the dataset should be restricted to authorized researchers, and stored data should be protected using appropriate access controls. Retention and deletion procedures should be defined before data collection.

AI recommendations should be treated as decision support rather than unquestionable decisions. Students should not be unfairly categorized or denied learning opportunities because of an algorithmic prediction. The evaluation should also consider whether recommendation behaviour differs systematically across learner groups.

Explainability is particularly important in an educational setting. A faculty member should be able to see the evidence behind a recommendation, such as repeated low scores in a topic or incomplete prerequisite activities. Human review should remain part of academic intervention.

Governance Requirements

Responsible deployment requires governance throughout the data lifecycle. Before collection, the study should define the purpose of each feature, the required permissions and consent procedures, retention periods, and access roles. During analysis, identifiers should be minimized or pseudonymized where possible. After the study, deletion or retention should follow the approved protocol.

Fairness should be considered as an evaluation dimension rather than an afterthought. Recommendation behaviour may differ across learner groups because of differences in data availability, prior preparation, engagement patterns, or resource access. The research should therefore inspect whether the system systematically provides less supportive learning opportunities to particular groups.

Explainability and Human Oversight

Explainability is especially relevant when recommendations influence what a learner studies next. The faculty interface should make it possible to inspect the evidence behind a recommendation and, where appropriate, override or supplement the automated suggestion. This human-in-the-loop design is consistent with the proposed role of AI as decision support rather than autonomous academic authority.

EXPECTED OUTCOMES

The expected outcome is an implementable framework for AI-supported personalized learning in higher education. The study is expected to provide: (1) a learner-profile representation using multiple learner characteristics; (2) an AI/ML-based personalization component; (3) a feedback mechanism for dynamic adaptation; (4) a faculty-support view of learner progress and weak areas; and (5) an evaluation methodology for measuring learning outcomes and recommendation quality.

These are proposed outcomes and should not be interpreted as experimental findings. Actual effectiveness will be established only after implementation, data collection, and empirical evaluation.

LIMITATIONS AND FUTURE WORK

The proposed framework depends on the quality, completeness, and availability of learner data. Learning behaviour can change over time, while resource preferences are not always easy to measure reliably. A model developed using data from one institution, discipline, or course may also have limited generalizability to other contexts.

Future work will involve developing a working prototype, collecting approved learning data, comparing alternative learner-profiling and recommendation techniques, and conducting empirical evaluation with UG and PG students. Longitudinal evaluation can examine whether personalization remains useful as learners progress through a course. Explainable recommendations can also be investigated so that students and faculty understand why particular resources are suggested.

Threats to Validity

Several threats should be considered during future validation. Construct validity may be affected if engagement or resource preference is represented by incomplete proxy measures. Internal validity may be affected by differences in course difficulty, instructor practice, or learner participation between comparison conditions. External validity may be limited if the study is conducted in one institution, discipline, or course. Reproducibility will also depend on the availability and quality of the approved dataset and learning resources.

These limitations do not invalidate the proposed framework; instead, they define the conditions under which its effectiveness should be tested. Reporting data characteristics, preprocessing decisions, model-selection criteria, and recommendation rules will be important for transparent replication.

CONCLUSION

AI provides an opportunity to support personalized learning in higher education, but effective personalization requires more than adding an AI tool to an existing course. Academic performance, learning behaviour, resource preferences, and changing learning needs should be considered together. This paper proposes a feedback-driven framework that combines these dimensions with an AI/ML personalization component and a faculty-support layer.

The proposed approach positions AI as an academic support mechanism rather than a replacement for faculty expertise. By returning assessment evidence to the learner profile, the system can adapt recommendations as learning progresses, while faculty members can use summarized insights to provide targeted intervention. The next stage of the research is empirical: implementation, approved data collection, model comparison, recommendation evaluation, and validation with UG and PG students.

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