AI Framework for Academic Progress Monitoring and Personalized Assignment Recommendation in Higher Education

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Abstract

The rapid development of Artificial Intelligence (AI) has significantly expanded its applications in higher education, particularly in the fields of learning analytics and personalized learning. Continuous monitoring of students' academic progress and providing personalized learning recommendations remain major challenges in higher education. This paper proposes an AI-assisted framework for academic progress monitoring and personalized assignment recommendation based on a Decision Tree classification model for predicting students' expected academic performance. The proposed approach integrates students' learning activities, formal assessment results, and historical instructor decisions to predict the expected grade category and automatically generate personalized assignments with an appropriate level of difficulty. A prototype of the framework was implemented in Python using the scikit-learn library and evaluated on a dataset of 50 students. Experimental results demonstrate that the proposed framework provides transparent and interpretable predictions, reduces the effort required for continuous monitoring of student progress, and supports the effective implementation of personalized learning. Rather than replacing instructor judgment, the proposed approach serves

as an intelligent decision-support tool that can be integrated into existing learning management systems and adapted to a wide range of higher education courses.

Keywords: Artificial Intelligence, Decision Tree, Educational Data Mining, Learning Analytics, Academic Progress Monitoring, Personalized Learning, Higher Education.

Introduction

Artificial intelligence (AI) is playing an increasingly important role in higher education by supporting data-driven educational decision-making and personalized learning. Advances in educational data mining and learning analytics have enabled institutions to collect, process, and analyze student performance data more effectively, providing valuable insights into learning processes and academic outcomes (Baker, 2010; Romero & Ventura, 2010; Siemens & Long, 2011). This study extends previous research on AI-assisted educational technologies and academic analytics (Tabatadze, 2024; Tabatadze & Khundadze, 2026), this study focuses on academic progress monitoring and personalized assignment recommendation.

Despite these developments, continuous monitoring of student progress remains a challenging task for university instructors. Student performance is typically assessed through multiple learning activities and formal assessments conducted throughout a course, requiring instructors to continuously evaluate diverse information in order to identify students who need additional academic support. In many cases, learning difficulties become evident only after formal assessments have taken place, reducing opportunities for timely intervention. Previous studies have therefore emphasized the importance of early prediction of student performance using educational data (Cortez & Silva, 2008; Kabakchieva, 2013; Marbouti et al., 2016).

Another challenge is determining the most appropriate learning activities once students requiring additional support have been identified. This often involves manually reviewing previous course topics, assignment difficulty levels, and prerequisite relationships, making personalized recommendations both time-consuming and potentially inconsistent.

To address these challenges, this study proposes an AI-assisted framework for academic progress monitoring and personalized assignment recommendation based on a Decision Tree classification model. The framework integrates students' learning activities, formal assessment results, and historical instructor decisions to predict expected grade categories and automatically generate personalized assignments with appropriate difficulty levels. Unlike many existing approaches that focus solely on predicting academic performance, the proposed framework combines prediction and recommendation within a unified architecture that supports instructors throughout the learning process.

The proposed approach makes three main contributions. First, it introduces a checkpoint-based framework that continuously updates student performance predictions as new assessment data become available. Second, it integrates predictive analytics with a transparent recommendation mechanism that automatically generates personalized assignments according to students' predicted performance. Third, it presents an experimental evaluation of the proposed framework using real educational data and demonstrates its practical applicability through quantitative analysis and representative case studies.

2. Literature Review

Artificial intelligence (AI) has become an important component of higher education, supporting academic administration, teaching, automated assessment, educational analytics, intelligent tutoring systems, and early identification of at-risk students (Tabatadze, 2024; Tabatadze, 2026; Tabatadze & Khundadze, 2026). Across these applications, AI primarily serves as a decision-support technology that assists instructors while preserving human oversight over educational decisions.

Educational Data Mining (EDM) and Learning Analytics (LA) provide the methodological foundation for AI-based educational systems. EDM applies machine learning and data mining techniques to identify patterns in educational data and predict student performance (Baker, 2010; Romero & Ventura, 2010), while Learning Analytics focuses on collecting and analyzing learner-generated data to improve teaching and learning processes (Siemens & Long, 2011). Previous studies have demonstrated that student engagement and participation are reliable indicators of academic success and support timely educational interventions (Romero et al., 2013; Baker & Inventado, 2014).

Student performance prediction is one of the most widely studied applications of machine learning in education. Numerous studies have successfully applied supervised learning methods to identify at-risk students using historical academic and behavioural data (Cortez & Silva, 2008; Kabakchieva, 2013; Marbouti et al., 2016). Among these methods, Decision Tree classifiers are particularly attractive because they combine satisfactory predictive performance with high interpretability, enabling instructors to understand the reasoning behind each prediction (Breiman et al., 1984; Quinlan, 1986; Al-Barrak & Al-Razgan, 2016; Kotsiantis, 2012).

Another important research direction is personalized learning, where instructional content and learning activities are adapted to individual students' knowledge and learning needs (Brusilovsky, 2001; Chrysafiadi & Virvou, 2013). Previous studies have demonstrated the effectiveness of personalized diagnosis, adaptive recommendation systems, and individualized learning pathways in improving learning outcomes (Chen, 2011; VanLehn, 2011). In a related direction, (Tabatadze and Sokhadze, 2023) showed that statistical analysis of collected assessment points can inform targeted improvements to course content.

Although significant progress has been made, most existing studies address student performance prediction and personalized learning separately. Few studies integrate these functions into a unified framework that continuously monitors academic progress while simultaneously generating personalized assignment recommendations. The framework proposed in this study addresses this gap by combining predictive analytics and adaptive assignment recommendation within a single checkpoint-based architecture that supports instructors throughout the learning process.

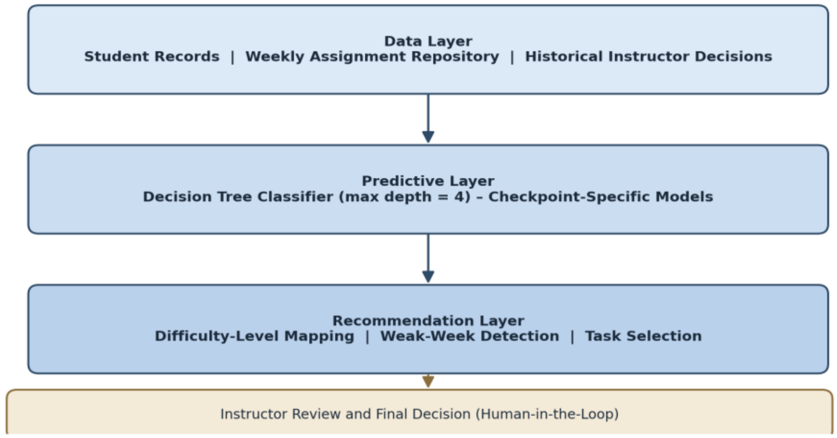
3. Proposed AI-Assisted Framework

3.1. Overall Framework

The proposed framework supports instructors in monitoring academic progress and generating personalized assignment recommendations at predefined checkpoints of a 17-week course, building on adaptive and student-modeling approaches that tailor instructional content to individual learners' estimated knowledge levels (Brusilovsky, 2001; Chrysafiadi & Virvou, 2013). The framework analyzes informal and formal assessment data to produce two outputs for each student to produce two outputs for each student: a predicted grade category and personalized assignment recommendations organized by topic and difficulty.

As illustrated in Figure 1, the framework comprises three components. The data layer stores weekly student records, a structured assignment repository, and historical instructor decisions used for model training. The predictive layer employs a Decision Tree classifier to estimate the expected grade category based on cumulative performance data available at each checkpoint. The recommendation layer translates the predicted grade into appropriate assignment difficulty levels, identifies topics requiring additional practice, and selects the corresponding assignments. The instructor retains full control over the final recommendations. The framework is implemented as a Python-based prototype using standard machine learning and data-processing libraries (Pedregosa et al., 2011).

Figure 1. Overall Framework Architecture

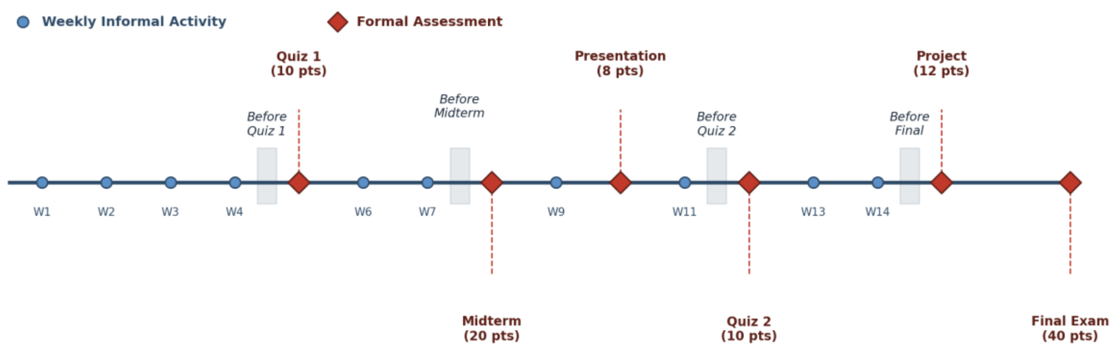


3.2. Dataset and Data Processing

The proposed framework operates on three categories of structured data: student records, the weekly assignment repository, and historical instructor decisions used to train the predictive model.

The student dataset used to evaluate the framework consists of 50 student records collected across a 17-week course. For each student, the dataset records weekly informal activity scores (on a 0-5 scale) for Weeks 1, 2, 3, 4, 6, 7, 9, 11, 13, and 14, together with the results of all formal assessment instruments: Quiz 1 (Week 5, maximum 10 points), the Midterm examination (Week 8, maximum 20 points), a Presentation (Week 10, maximum 8 points), Quiz 2 (Week 12, maximum 10 points), a Project (Week 15, maximum 12 points), and the Final examination (Week 17, maximum 40 points), for a total of 100 points. Figure 2 illustrates the course timeline and the points at which informal activity and formal assessment data are collected relative to each checkpoint.

Figure 2. Course Timeline and Data Collection Process



The weekly assignment repository organizes practical tasks for ten teaching weeks (Weeks 1, 2, 3, 4, 6, 7, 9, 11, 13, and 14), corresponding to individual course topics. Each week's assignments are categorized into four difficulty levels, Easy, Medium, Hard, and Complex, identified by task number. In addition, each week is annotated with its thematic prerequisite weeks (topic dependencies), reflecting the sequential structure of the syllabus.

A historical decision dataset, produced by the instructor for the Before-Midterm checkpoint, records the informal progress percentage, official assessment percentage, resulting grade category, and recommended tasks for each of the 50 students. This dataset serves as the training data (ground truth) for the predictive model at that checkpoint; analogous historical decisions are required to train the model at the remaining three checkpoints, and their collection is identified as a direction for future work in Section 6.

Grade categories follow a seven-level scale: A - Excellent (91-100%), B - Very Good (81-90%), C - Good (71-80%), D - Satisfactory (61-70%), E - Sufficient (51-60%), Fx - Fail, Retake (41-50%), and F - Fail (0-40%). Table 1 summarizes the experimental dataset used to evaluate the Before-Midterm checkpoint of the proposed framework.

Table 1. Summary of the Experimental Dataset

Dataset	Number of Records	Description
Student Records	50	Weekly informal activity scores and formal assessment results (Quiz 1, Midterm, Presentation, Quiz 2, Project, Final)
Weekly Assignments	10 weeks	Practical tasks organized by topic, difficulty level, and topic dependency
Historical Decisions (Before Midterm)	50	Instructor-labeled grade categories (7 levels, including Fx) and recommended tasks used for model training

3.3. Predictive Modeling of Academic Performance

The core predictive component of the framework is a Decision Tree classifier (maximum depth of four), trained separately at each of four course checkpoints: before Quiz 1, before the Midterm, before Quiz 2, and before the Final examination, following prior evidence that decision tree models can effectively predict a student's final grade from earlier-available performance indicators (Al-Barrak & Al-Razgan, 2016). Each checkpoint is associated with a cumulative feature set that grows as the semester progresses, reflecting the assessment information available to the instructor at that point in the course. Table 2 summarizes the feature configuration of each checkpoint.

Table 2. Feature Configuration at Each Course Checkpoint

Checkpoint	Cumulative Features Used for Prediction	Weeks Covered
Before Quiz 1	Weekly activity (Weeks 1-4)	1-4
Before Midterm	+ Quiz 1 result	1-4, 6-7

Before Quiz 2	+ Midterm, Week 9 activity, Presentation, Week 11 activity	1-4, 6-7, 9, 11
Before Final	+ Quiz 2, Weeks 13-14 activity, Project	1-4, 6-7, 9, 11, 13-14

For each checkpoint, the classifier is trained on the historical decision dataset associated with that checkpoint, using the cumulative activity and assessment features listed in Table 2 as predictors and the instructor-assigned grade category as the target label. At prediction time, a new student's record, containing only the features available at the given checkpoint, is passed to the corresponding trained model, which returns a predicted grade category (e.g., A - Excellent, C - Good, F - Fail). Because each checkpoint has its own model and feature set, a new student need not appear in the historical training data; the model generalizes the relationship between informal and formal performance and grade outcome observed in past cohorts.

Before prediction, all input data undergo validation to ensure that required columns are present, that all feature values are numeric, that weekly activity scores fall within the 0-5 range, and that quiz results fall within their respective valid ranges. This validation step reduces the risk of erroneous predictions caused by malformed input data.

3.4. Difficulty-Level Mapping and Adaptive Task Recommendation

Once a student's grade category has been predicted, the framework translates this prediction into a personalized set of recommended assignments through two sequential steps, difficulty-level mapping and relevant-week detection, following the general logic of personalized diagnosis and remedial learning systems that pair a diagnosis of a learner's weaknesses with a matched set of remedial materials (Chen, 2011).

In the difficulty-level mapping step, the predicted grade category is mapped to a pair of recommended difficulty levels. Students predicted to achieve grades in the A or B range are directed toward Hard and Complex tasks, reflecting readiness for more demanding material. Students predicted in the C or D range are directed toward Medium and Hard tasks, while students predicted at the E category or below are directed toward Easy and Medium tasks, prioritizing foundational reinforcement over advanced material.

In the relevant-week detection step, the framework examines the student's weekly informal activity scores across the weeks covered by the current checkpoint and flags any week in which activity is at or below a low-engagement threshold (a score of 2 out of 5) as a week requiring review. If no week falls below this threshold, the framework defaults to the two most recent weeks of the checkpoint, ensuring that a recommendation is always produced even for consistently engaged students.

Finally, for each flagged week and each recommended difficulty level, the framework selects a small number of specific task numbers (two, by default) from the weekly assignment repository, producing a structured, individualized list of recommended assignments organized by week and difficulty level. The generated recommendation is intended to narrow the scope of the instructor's manual review rather than to serve as an automatic or final assignment; the instructor retains full discretion over what guidance is ultimately communicated to the student.

3.5. Framework Demonstration and Case-Based Evaluation

To further demonstrate the practical applicability of the proposed framework across the full course timeline, five representative student cases were examined at different checkpoints: two cases before the Midterm, one case before Quiz 2, and two cases before the Final examination. These cases were also used as the basis for a practical group activity, in which participants were asked to manually determine relevant weeks, difficulty levels, and specific task recommendations for the same student profiles, prior to comparing their judgment against the framework's output. Table 3 summarizes the framework's generated output for each case.

Table 3. Case-Based Demonstration of the Framework Across Course Checkpoints

Case (Checkpoint)	Informal Progress	Official Assessment	Predicted Grade	Recommended Difficulty

Case 1 (Before Midterm)	36.7%	40.0%	F - Fail (0-40%)	Easy, Medium
Case 2 (Before Midterm)	83.3%	90.0%	B - Very Good (81-90%)	Hard, Complex
Case 3 (Before Quiz 2)	57.5%	65.8%	D - Satisfactory (61-70%)	Easy, Medium, Hard
Case 4 (Before Final)	42.0%	63.3%	E - Sufficient (51-60%)	Easy, Medium
Case 5 (Before Final)	66.0%	78.3%	C - Good (71-80%)	Medium, Hard

The five cases illustrate that the framework's recommendations scale consistently with combined student progress, and adapt both the number of flagged weeks and the recommended difficulty range accordingly. For students with consistently low engagement and assessment results (Case 1), the framework concentrates recommendations on Easy and Medium tasks across a wider set of weeks. For strong-performing students (Case 2), recommendations shift toward Hard and Complex tasks concentrated on fewer, more recent weeks. Cases involving later checkpoints (Cases 3 to 5) demonstrate that the framework continues to integrate an expanding set of formal assessment results, such as the Midterm, Presentation, Quiz 2, and Project, as the course progresses, without requiring separate manual reconfiguration.

The comparison between the framework's automatically generated recommendations and the manually produced recommendations from the group activity indicated general agreement on the weeks and difficulty levels most relevant to each student profile, while manual recommendations occasionally emphasized additional contextual considerations that fall outside the scope of the available quantitative indicators, such as a student's demonstrated conceptual understanding during class discussion.

Conclusion

The continuous monitoring of student progress across a multi-stage assessment structure places substantial demands on instructors, particularly in courses with large cohorts and recurring assessment checkpoints. This study proposed an AI-assisted framework for personalized academic progress monitoring and adaptive assignment recommendation, built around a Decision Tree classifier trained separately at four checkpoints of a 17-week course: before Quiz 1, before the Midterm, before Quiz 2, and before the Final examination.

The framework combines weekly informal activity indicators with cumulative formal assessment results to predict a student's expected grade category, and translates this prediction into a personalized set of recommended assignments, differentiated by difficulty level and organized by weekly topic. The main contribution of this study is the integration of predictive grade estimation and adaptive task recommendation into a single, checkpoint-based framework that mirrors the natural rhythm of a semester-long course.

The Python-based prototype and the evaluation on a dataset of 50 students, together with case-based demonstrations spanning all four checkpoints, indicate the feasibility of the proposed approach. The current framework relies on quantitative indicators alone and does not account for qualitative aspects of student engagement, such as classroom participation quality or conceptual understanding observed during instruction, which instructors continue to evaluate independently.

Future research will focus on training and validating the framework using historical decision data for the remaining checkpoints (before Quiz 1, before Quiz 2, and before the Final examination), expanding the student dataset across multiple cohorts, and comparing the Decision Tree approach with alternative predictive models. Further development may also include integration of the framework into a learning management system as an auxiliary instructor-facing module, building on prior work on visualizing student data within the Moodle platform

(Tabatadze, 2023), alongside systematic evaluation of its effect on student outcomes and instructor workload.

Overall, the proposed framework provides a practical foundation for introducing AI-assisted decision support into the recurring task of academic progress monitoring, while preserving instructor oversight and responsibility for all pedagogical decisions.

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