PERSONALIZED ACADEMIC INTERVENTIONS USING ADAPTIVE AND EXPLAINABLE AI: MULTI-MODAL LEARNING ANALYTICS FRAMEWORK

25-26J-172

Project Proposal Report

Disanayaka S.T

(IT22370228)

Supervised by – Ms. Sanjeevi Chandrasiri

B.Sc. (Hons) Degree in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

Sri Lanka

August 2025

Design and Implementation of a Real-Time Student Risk Prediction System Using Adaptive Ensemble Learning with Gamified Recommendations

25-26J-172

Project Proposal Report

B.Sc. (Hons) Degree in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology
Sri Lanka

August 2025

DECLARATION

I declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Name	Student ID	Signature
Disanayaka S.T.	IT22370228	

The supervisor/s should certify the proposal report with the following declaration.

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

29/08/2025

Signature of the supervisor: Date

(Ms. Sanjeevi Chandrasiri)

ABSTRACT

Student risk prediction systems have advanced significantly, providing insights into learners who are likely to underperform. However, a persistent gap exists between predicting risks and ensuring that students act on recommended interventions. Many systems provide explanations or risk scores but fail to sustain motivation among students to follow improvement plans.

This research proposes the development of a **Recommendation and Gamification Module** that builds upon predictive risk models to provide personalized interventions, reinforced through engaging game-like features. The system delivers actionable recommendations (e.g., improving attendance, timely assignment submission, active participation) and integrates gamification elements such as progress tracking, badges, challenges, and rewards to enhance student motivation. An interactive dashboard allows learners to monitor their academic journey, visualize milestones, and receive continuous feedback, while educators gain insights into student progress.

By combining prescriptive analytics with gamification, the proposed system transforms recommendations into achievable and enjoyable tasks, ensuring higher adherence and improved learning outcomes. This approach addresses a critical gap in current educational AI frameworks, where motivation and behavioral reinforcement are often overlooked. The outcome will be a dynamic, student-centered support platform that fosters sustained academic engagement and success.

Keywords — Gamification, Academic Interventions, Personalized Recommendations, Student Motivation, Educational Analytics

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

The application of predictive analytics in education has evolved into a critical tool for identifying students at academic risk [1], [2]. By analyzing multimodal data such as attendance, grades, and online learning management system (LMS) interactions, institutions can detect early warning signals and intervene proactively. Despite their growing accuracy, most predictive systems provide only alerts or risk scores, leaving students and educators without practical guidance [3]. Furthermore, recommendations are often generic and lack personalization, which reduces their usefulness [5]. As a result, students tend to ignore interventions, viewing them as burdensome or irrelevant [6].

To address this limitation, recent studies have explored integrating motivational strategies into educational interventions. Gamification, which applies game elements such as progress tracking, badges, and rewards, has shown promise in enhancing learner engagement and sustaining behavioral change [7]–[9]. However, most existing implementations focus either on prediction or on motivation in isolation, resulting in fragmented solutions [10].

This research proposes a **Recommendation and Gamification Module** that unifies risk prediction, personalized guidance, and motivational elements. Unlike prior systems, the proposed framework transforms predictive insights into actionable recommendations enhanced with gamified features. Students are thus encouraged not only to acknowledge their risks but also to actively engage in addressing them. Educators benefit from integrated dashboards that provide real-time monitoring of risks, recommendations, and progress. By bridging predictive and prescriptive analytics with motivation-driven design, this work introduces a novel approach that supports sustainable academic improvement.

1.1 Background & Literature Survey

The rapid growth of learning analytics has transformed how educational institutions monitor, evaluate, and improve student performance. Early studies, such as Siemens and Long [1], emphasized the potential of data-driven analytics in identifying at-risk learners and guiding institutional planning. Building on this, more recent work highlights the ability of machine learning and multimodal analytics to detect behavioral and academic risk factors by leveraging diverse data sources such as attendance, grades, LMS interactions, and even socio-behavioral indicators [2], [3].

However, while predictive models provide accurate early warnings, their **practical impact on student learning remains limited**. As Papamitsiou and Economides [5] noted, predictive systems frequently produce generic recommendations such as "study harder" or "review lecture materials," which students often perceive as vague and unhelpful. Nguyen et al. [6] further highlight that interventions lacking personalization are rarely adopted, thereby diminishing the effectiveness of risk analytics.

Parallel to these developments, research on **gamification in education** has gained traction as a mechanism for enhancing motivation and engagement. Studies have shown that embedding game elements, such as rewards, badges, challenges, and leaderboards, can significantly improve learner participation and commitment [7], [9], [11]. Hamari et al. [7] conducted an extensive review of empirical evidence demonstrating the positive impact of gamification on both short-term engagement and long-term academic achievement. Similarly, Sailer et al. [11] discuss the psychological drivers behind gamified interventions, including intrinsic motivation, self-determination, and sustained engagement.

Despite this evidence, gamification and predictive analytics have largely developed in **parallel streams** rather than as an integrated framework. Most predictive systems remain reactive, identifying risks but offering limited motivational support, while gamified systems tend to focus on increasing general engagement without linking tasks to predictive academic insights [10]. This gap underscores the need for a holistic

approach where **risk detection, actionable recommendations, and motivation mechanisms are tightly coupled**.

Thus, while existing literature has demonstrated the effectiveness of both predictive modeling and gamification independently, **few studies attempt to unify the two** into a cohesive model that transforms risk alerts into actionable, motivating, and measurable interventions. The proposed Recommendation and Gamification Module addresses this limitation by introducing a framework that combines predictive accuracy, prescriptive guidance, and gamified reinforcement to drive meaningful academic improvement.

1.2 Research Gap

Although predictive analytics has matured significantly, its application in education reveals persistent shortcomings that reduce its practical effectiveness. The most pressing gap lies in the **transition from awareness to action**. Existing systems excel at identifying at-risk students [1], [3], yet they provide limited follow-up in the form of actionable, context-specific recommendations. Students are frequently left with **generic interventions** such as "study more" or "revise lessons," which fail to consider individual needs or learning contexts [5]. Consequently, learners perceive these systems as unhelpful, leading to disengagement and low adoption rates [6].

Another gap lies in **student motivation and sustained engagement**. Research in psychology and education confirms that motivation is a critical determinant of learning success [7], [11]. Yet, most predictive frameworks lack mechanisms to keep students consistently engaged in following recommendations. While gamification has been shown to significantly improve motivation and academic persistence [7], [9], its implementation is often **isolated from predictive systems**, serving as a general engagement tool rather than a targeted academic support mechanism [10].

A third gap is **fragmentation**. Current solutions often treat risk prediction, recommendations, and motivation as **separate domains**, leading to piecemeal

interventions. For example, predictive models may flag a student as at-risk, but the recommendation system delivers generic tasks, and gamification—if applied at all—functions independently of the prediction model [8]. This lack of integration prevents a seamless feedback loop where prediction drives personalized recommendations and gamification ensures adherence.

The **novelty of this research** lies in bridging these gaps through a **unified framework** that couples predictive analytics with prescriptive and motivational strategies. By embedding gamification principles—progress tracking, challenges, rewards, and badges—directly into personalized recommendations, the system ensures that learners are not only informed of their risks but also motivated and rewarded for addressing them. Furthermore, educators gain actionable insights through dashboards that track student progress, enabling timely and targeted interventions.

This research therefore advances beyond fragmented approaches by creating a **holistic ecosystem** that connects prediction, recommendation, and motivation. It transforms risk detection from a passive alert mechanism into an **active, engaging, and sustainable pathway for academic improvement**, addressing a long-standing gap in the learning analytics domain.

Feature	**Existing Research Methods**	**Proposed Method**
Recommendations	Generic advice such as "study more" [5]	Personalized, adaptive recommendations tailored to individual learning needs
Motivation	Minimal focus; low student engagement [6], [7]	Gamified tasks (badges, rewards, progress tracking, challenges) [9]

System Integration	Prediction and motivation treated separately [8], [10]	Unified framework combining prediction, recommendation, and gamification
Feedback Loop	Limited feedback on student progress [3]	Continuous monitoring with dynamic feedback for students and educators
Adaptability	Static recommendations; no adjustment to student progress [5]	Adaptive interventions updated based on performance and ongoing behavior

Table 1 Comparison between Existing Research Methods and Proposing Method

1.3 Research Problem

Despite significant progress in predictive modeling, a critical challenge persists: the gap between identifying academic risks and ensuring that students take effective, sustained action. Current systems excel at **detection** but fall short at **intervention**. Students frequently disregard generic recommendations, perceiving them as irrelevant or overly simplistic [5], [6]. Moreover, without motivational reinforcement, interventions remain underutilized, diminishing their long-term effectiveness [7].

This limitation creates an urgent research problem: predictive analytics alone cannot guarantee academic improvement unless coupled with strategies that drive engagement and behavioral change. Prior research has explored prescriptive analytics [3] and gamification [7], [9], yet these efforts have largely been **fragmented**, treating prediction, recommendation, and motivation as separate domains [8], [10]. Such siloed approaches fail to produce a comprehensive framework that supports both students and educators.

The **research problem** can therefore be articulated as follows:

“How can a recommendation system enhanced with gamification be designed to bridge the gap between risk prediction and student behavioral change, ensuring that at-risk learners are motivated, guided, and reinforced to achieve sustainable academic improvement?”

Addressing this problem requires not only unifying predictive and prescriptive analytics but also embedding motivational design principles into interventions. This integration forms the **novelty** of the proposed research, contributing a comprehensive model that transforms risk awareness into actionable, engaging, and trackable academic improvement strategies [9], [11].

2. OBJECTIVES

2.1 Main Objective

To design and implement a recommendation and gamification module that transforms risk predictions into personalized, engaging, and trackable academic interventions, thereby improving student motivation, adherence, and performance.

2.2 Specific Objectives

To review existing predictive models and identify their limitations in motivating students.

To develop a recommendation engine that generates actionable, personalized academic interventions.

To integrate gamification elements (badges, challenges, progress tracking, rewards) into the system.

To design a dashboard for students and educators to monitor risks, recommendations, and achievements.

To evaluate the system's effectiveness in improving student engagement and learning outcomes.

3. METHODOLOGY

3.1 Technologies

The proposed Recommendation and Gamification Module will be developed using a combination of modern technologies to ensure scalability, usability, and maintainability. The system will be designed as a full-stack application with the following planned technologies:

- **Frontend Development:** The user interfaces for the Student and Educator Dashboards will be developed using **React.js** with **Tailwind CSS**, ensuring a dynamic, responsive, and user-friendly experience.
- **Backend Development:** The server-side logic and APIs will be implemented using **Node.js and Express.js**, providing a lightweight and efficient runtime to connect predictive models, the recommendation engine, and dashboards.
- **Database: MongoDB** will be used as the primary database to store student profiles, academic records, recommendations, gamification data, and progress tracking. Its flexibility will support multimodal educational data.
- **Integration with Prediction Models:** The system will integrate with **AI/ML-based academic risk prediction models**, which analyze attendance, grades, and LMS activity to generate risk scores.
- **Gamification Layer:** A dedicated module will be developed to embed badges, challenges, progress tracking, and rewards into the recommendation system to increase student motivation.
- **Prototyping and Design: Figma** will be used for prototyping and designing system interfaces before implementation.
- **Testing and Evaluation:** After development, the system will undergo **functional and non-functional testing**, ensuring accuracy, performance, and usability before deployment.

This methodology outlines the planned technological framework for the proposed system, ensuring that it will effectively address the identified research problem and support both students and educators in improving academic outcomes.

3.2 System Overview Diagram

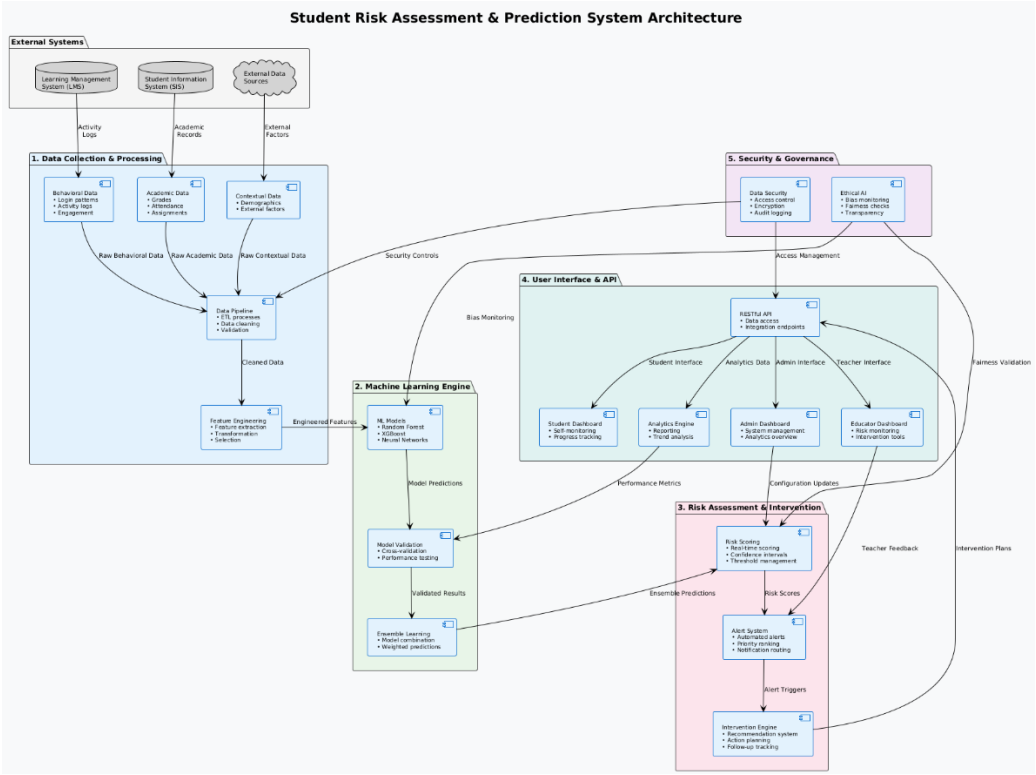


Figure 1 System Overview Diagram

3.3 Component Diagram

The **Component Diagram** illustrates the structural view of the proposed Recommendation and Gamification Module. It identifies the major system components, their responsibilities, and the interfaces that allow them to interact.

- **Risk Prediction Module (External Component):** This component provides student risk scores based on academic and behavioral data such as attendance, grades, and LMS activity. It acts as an input source for the recommendation system.
- **Recommendation Engine:** This core component processes risk scores and generates personalized, actionable interventions. Unlike generic alerts, the engine tailors advice to the student's academic profile, learning patterns, and past performance.
- **Gamification Layer:** Built on top of the recommendation engine, this component enhances interventions with gamified elements such as badges, progress bars, challenges, and rewards. Its role is to transform recommendations into engaging tasks, fostering sustained motivation.
- **Student Dashboard:** This interface allows students to view their academic risks, receive personalized interventions, and monitor progress. It also displays gamification features such as badges earned and milestones achieved.
- **Educator Dashboard:** This interface provides educators with consolidated insights into student risks, engagement levels, and intervention outcomes. It supports decision-making by offering analytics and progress reports.
- **Notification and Feedback Component:** Responsible for delivering timely alerts to students (e.g., deadlines, reminders) and capturing feedback from both students and educators. Feedback is sent back to the recommendation engine for refinement.
- **Database Component:** Stores student profiles, academic records, recommendations, gamification data, and system logs. It ensures secure and reliable data management.

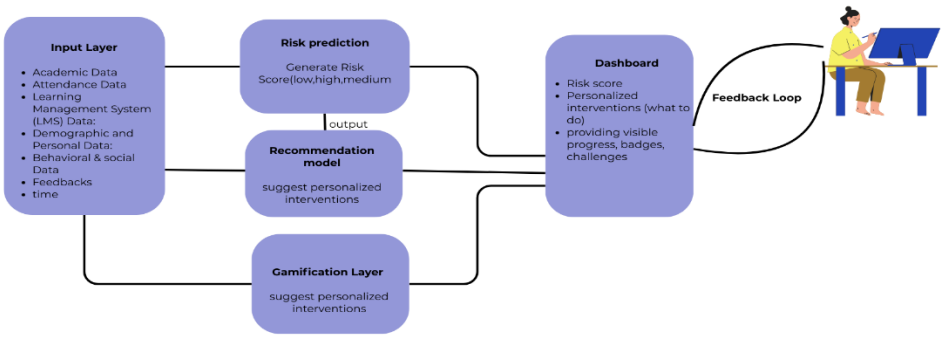


Figure 2 Component Diagram

3.4 Work Breakdown Structure

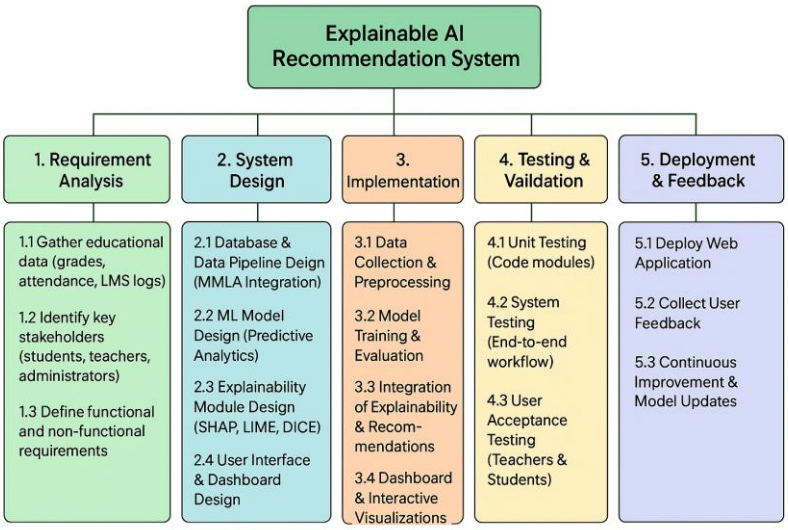


Figure 3 Work Breakdown Structure

4. GANTT CHART

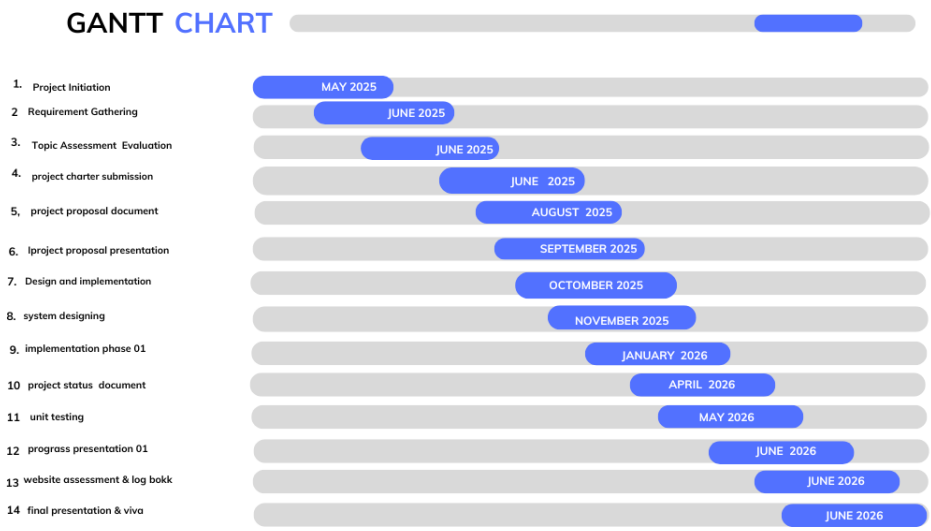


Figure 4 Gantt Chart

5. PROJECT REQUIREMENTS

5.1 Functional Requirements

- The system shall integrate with existing academic risk prediction models to retrieve at-risk student data.
- The system shall generate personalized, actionable academic recommendations tailored to each student.
- The system shall incorporate gamification elements such as progress tracking, challenges, badges, and rewards.
- The system shall provide a **Student Dashboard** displaying risks, recommendations, achievements, and progress.
- The system shall provide an **Educator Dashboard** presenting student risk analytics, engagement reports, and intervention tracking.
- The system shall update student progress dynamically based on completed tasks and modify recommendations accordingly.

- The system shall deliver timely alerts and notifications (deadlines, progress reminders, new challenges).

5.2 Non-Functional Requirements

- The system shall respond within 2 seconds for all dashboard operations under normal load.
- The system shall support scaling to at least 1,000 concurrent student users.
- The interface shall be intuitive, mobile-friendly, and require minimal training.
- The system shall use encrypted communication (HTTPS) and role-based access control
- The system shall comply with relevant regulations (GDPR/FERPA) to ensure ethical handling of student data.

5.3 Expected Test Cases

Test Case ID	**Description**	**Expected Outcome**
TC01	Verify system retrieves student risk data from prediction model.	Risk score for the student is displayed on the dashboard.
TC02	Verify personalized recommendations are generated for at-risk students.	Student receives context-specific academic interventions (e.g., “attend tutorial,” “revise module”).
TC03	Verify gamification badge allocation when a student completes a task.	Badge is unlocked, progress bar updated, and reward displayed.

TC04	Verify Student Dashboard displays all required elements.	Dashboard shows risk level, recommendations, progress bar, and achievements.
TC05	Verify Educator Dashboard shows student analytics.	Educator can view risk scores, interventions, and engagement statistics.
TC06	Verify notification/alert system sends reminders for pending tasks.	Student receives notification message (e.g., "Your assignment task is due tomorrow").

Table 2 Expected Test Cases

6. DESCRIPTION OF PERSONAL AND FACILITIES

Registration Number	Name	Description
IT22370228	Disanayaka S.T	Responsible for requirement gathering and analysis, system design using UML diagrams, and implementation of the Recommendation & Gamification Module. Contributed to the development of student and educator dashboards, and participated in testing and documentation. Facilities used include **React.js, Node.js, Tailwind CSS, MongoDB, Firebase, Spring Boot, Visual Studio Code, and Figma** for design and development, along with institutional servers and datasets for testing and evaluation.

Table 3 Description of Personal And Facilities

7. BUDGET AND BUDGET JUSTIFICATION

7.1 Roughly Estimated Budget

Item	Description	Estimated Cost (LKR)
Software Licenses & Tools	Premium development tools, API testing tools, data visualization packages	12,000
Cloud Services	Cloud storage, computing for model training and deployment (AWS/Firebase/Azure) sharing among members	28,000
Internet & Miscellaneous	High-speed internet, backup drives, office supplies	5,000
Total Expenses		45,000

Table 4 Roughly Estimated Budget

7.2 Budget Justification

- **Software Licenses & Tools:** Premium licenses for essential software including API testing tools like Postman (professional version), enhanced data visualization libraries, and development environments to facilitate efficient coding, testing, and deployment.

- **Cloud Services:** Allocation for cloud infrastructure that supports scalable storage, machine learning model training, and deployment of RESTful APIs. This enables handling of large datasets and real-time processing needs without upfront heavy investment in physical servers.

- **Internet & Miscellaneous:** Supports reliable high-speed internet connectivity critical for continuous cloud service interaction, data transfer, and remote collaboration, along with backup devices for data safety and minor office consumables.

8. REFERENCE LIST

[1] G. Siemens and P. Long, “Penetrating the fog: Analytics in learning and education,” *EDUCAUSE Review*, vol. 46, no. 5, pp. 30–32, 2011.

[2] W. van der Aalst, “Process mining and learning analytics,” in *Handbook of Learning Analytics*, pp. 120–131, 2016.

[3] D. Ifenthaler and J. Y. Yau, “Utilising learning analytics to support study success in higher education: A systematic review,” *Educational Technology Research and Development*, vol. 68, no. 4, pp. 1961–1990, 2020.

[4] S. D’Mello and A. C. Graesser, “Feeling, thinking, and computing with affect-aware learning technologies,” in *The Cambridge Handbook of Computing Education Research*, pp. 419–444, 2015.

[5] Z. Papamitsiou and A. A. Economides, “Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence,” *Educational Technology & Society*, vol. 17, no. 4, pp. 49–64, 2014.

[6] Q. Nguyen, B. Rienties, and L. Toetenel, “Mixing and matching learning design and learning analytics,” *Learning, Media and Technology*, vol. 42, no. 1, pp. 32–45, 2017.

[7] J. Hamari, J. Koivisto, and H. Sarsa, “Does gamification work? – A literature review of empirical studies,” in *Proc. 47th Hawaii Int. Conf. System Sciences*, pp. 3025–3034, 2014.

[8] D. Werbach and D. Hunter, *For the Win: How Game Thinking Can Revolutionize Your Business*. Philadelphia, PA: Wharton Digital Press, 2012.

[9] A. Domínguez, J. Saenz-de-Navarrete, L. de-Marcos, L. Fernández-Sanz, C. Pagés, and J. J. Martínez-Herráiz, “Gamifying learning experiences: Practical implications and outcomes,” *Computers & Education*, vol. 63, pp. 380–392, 2013.

[10] J. Koivisto and J. Hamari, “The rise of motivational information systems: A review of gamification research,” *Int. J. Inf. Manage.*, vol. 45, pp. 191–210, 2019.

[11] M. Sailer, J. Hense, H. Mandl, and M. Klevers, “Psychological perspectives on motivation through gamification,” *Interaction Design and Architecture Journal*, vol. 33, pp. 28–37, 2017.

[12] V. J. Shute and F. Ke, “Games, learning, and assessment,” in *Assessment in Game-Based Learning*, pp. 43–58, 2012.

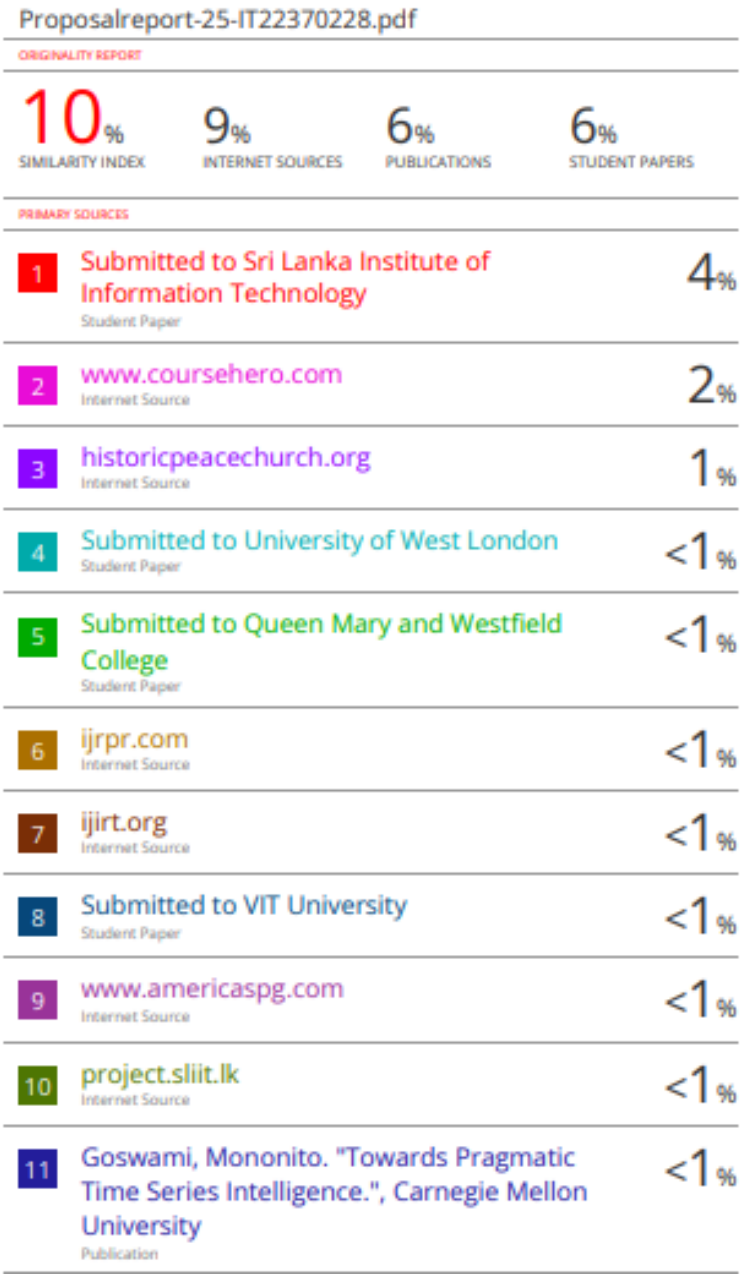
[13] C.-H. Su and C.-H. Cheng, “A mobile gamification learning system for improving learning motivation and achievements,” *J. Comput. Assist. Learn.*, vol. 31, no. 3, pp. 268–286, 2015.

[14] K. M. Kapp, *The Gamification of Learning and Instruction: Game-Based Methods and Strategies for Training and Education*. San Francisco, CA: John Wiley & Sons, 2012.

[15] M. Zhou, “Chinese university students’ acceptance of MOOCs: A self-determination perspective,” *Computers & Education*, vol. 92, pp. 194–203, 2016.

9. APPENDICES

9.1 Turnitin Report



Proposalreport-25-IT22370228.pdf

ORIGINALITY REPORT

10%	9%	6%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Sri Lanka Institute of Information Technology Student Paper	4%
2	www.coursehero.com Internet Source	2%
3	historicpeacechurch.org Internet Source	1%
4	Submitted to University of West London Student Paper	<1%
5	Submitted to Queen Mary and Westfield College Student Paper	<1%
6	ijrpr.com Internet Source	<1%
7	ijirt.org Internet Source	<1%
8	Submitted to VIT University Student Paper	<1%
9	www.americaspg.com Internet Source	<1%
10	project.sliit.lk Internet Source	<1%
11	Goswami, Mononito. "Towards Pragmatic Time Series Intelligence.", Carnegie Mellon University Publication	<1%

Figure 5 Turnitin Report

9.2 System User Interfaces

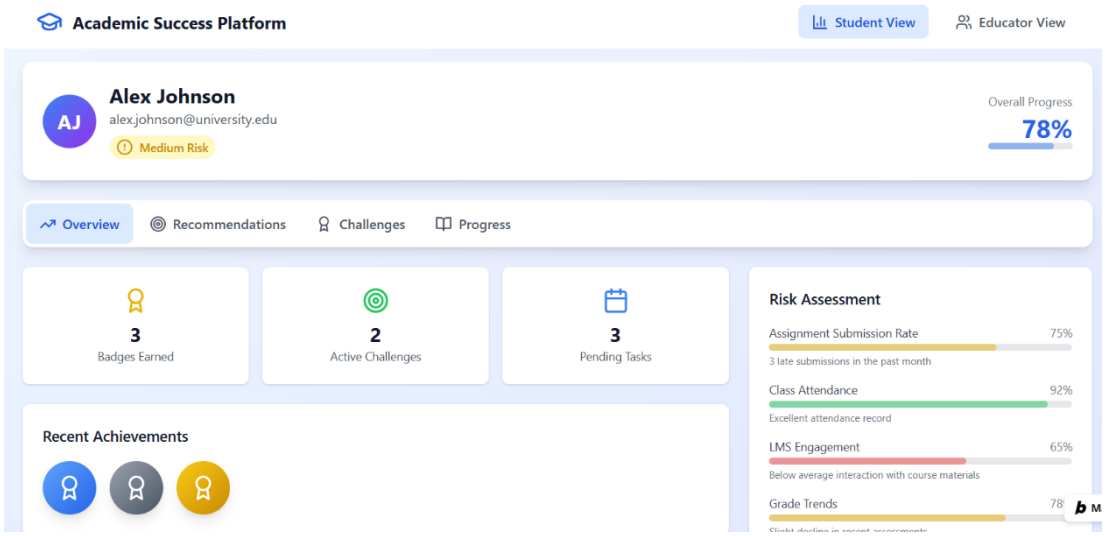


Figure 6

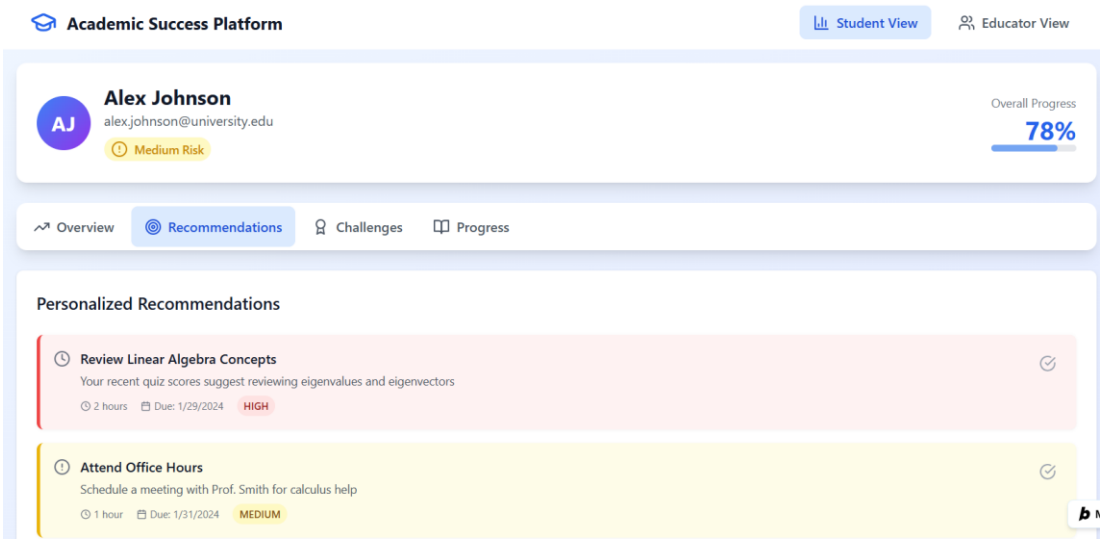


Figure 7

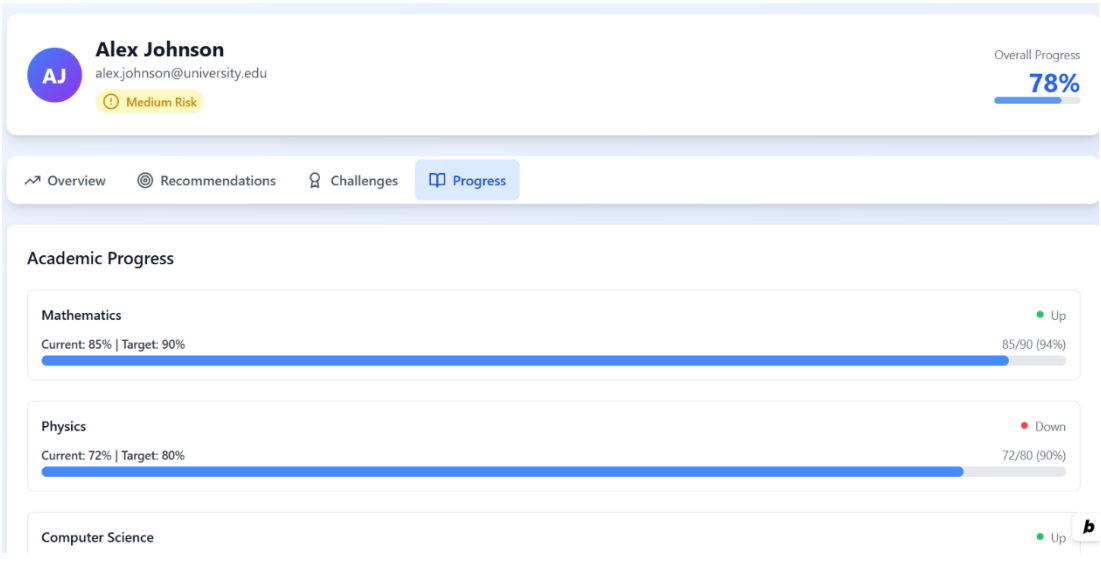


Figure 8

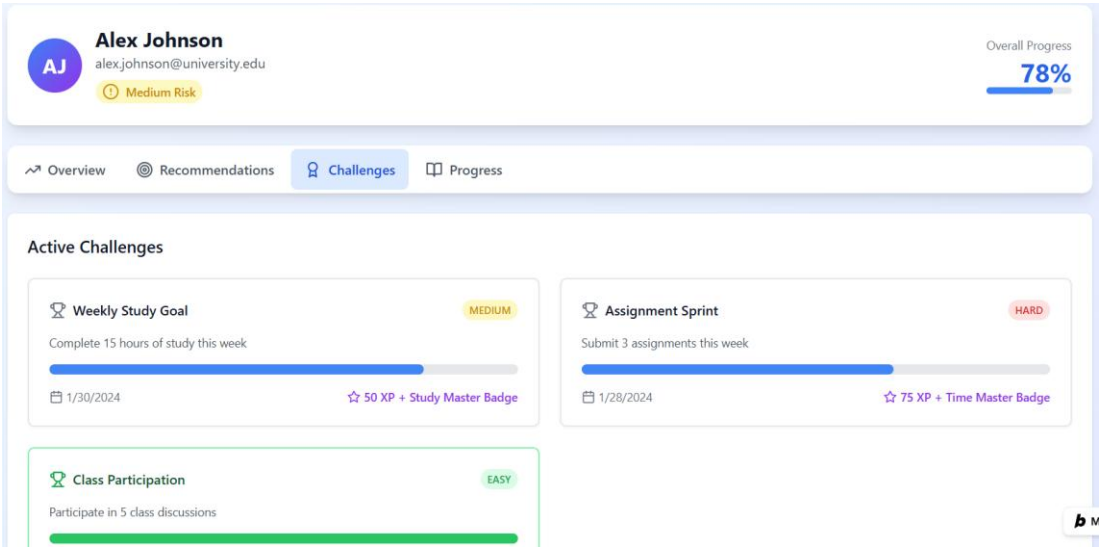


Figure 9

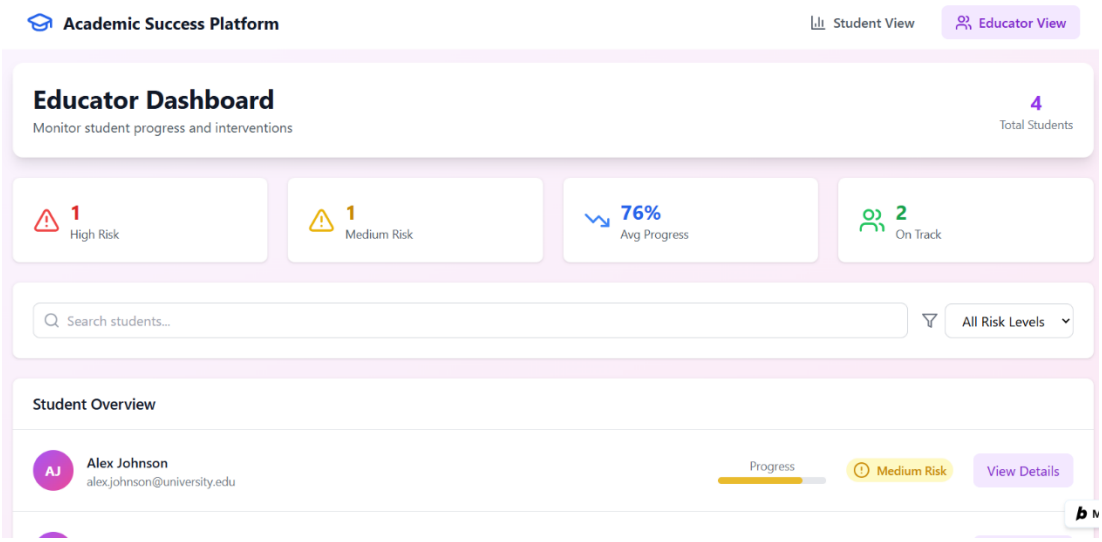


Figure 10