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

25-26J-172

Project Proposal Report

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B.Sc. (Hons) Degree in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

Sri Lanka

August 2025

Design and Development of An Adaptive Penalty-Augmented Ensemble Machine Learning Engine with Explainable AI for Real-Time Student Risk Prediction and Personalized Academic Interventions

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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
Ravisanka U.V.P	IT22354792	

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.

Signature of the supervisor: 29/08/2025 Date

(Ms. Sanjeevi Chandrasiri)

ABSTRACT

The need for precise, comprehensible, and flexible tools that can identify students at risk of academic failure or dropout has increased with the rise of data-driven education. In order to integrate and analyze multi-dimensional academic and behavioral data, this study presents an Intelligent Student Risk Assessment and Prediction Engine that makes use of ensemble machine learning techniques, such as Random Forest and XGBoost. To improve prediction accuracy and contextual relevance, the engine uses sophisticated feature engineering and a brand-new dynamic risk scoring algorithm that adjusts in real time to institutional patterns and academic trends throughout the year.

Thorough data preprocessing, multi-source feature integration, and model validation using retrospective backtesting and stratified cross-validation against previous student cohorts are all included in the methodology. In order to enable educators and administrators to implement prompt, evidence-based interventions, real-time risk scores are provided through secure RESTful APIs and displayed in an interactive dashboard. Improved early identification rates of at-risk students are anticipated, along with an increase in actionable insights for stakeholders and prediction accuracy that is predicted to outperform traditional static models by 18 to 22%.

The engine's scalability, ethical adherence to privacy regulations (such as the GDPR), and integration potential with current educational ecosystems will all be covered in the conclusions. To ensure practical utility and adoption, recommendations place a strong emphasis on ongoing retraining and pilot testing to improve thresholds and take stakeholder input into account. By connecting cutting-edge machine learning with practical teaching techniques, this work advances educational analytics and promotes individualized support that can enhance student success and retention.

Keywords: Student Risk Assessment, Ensemble Machine Learning, Dynamic Risk Scoring, Educational Data Analytics, Early Warning System

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
GDPR	General Data Protection Regulation
LMS	Learning Management System
ML	Machine Learning
RF	Random Forest
XGBoost	Extreme Gradient Boosting
TAFF	Thesis Approval and Feedback Form
REST	Representational State Transfer
NFR	Non-Functional Requirements
FR	Functional Requirements
KPI	Key Performance Indicator

1. INTRODUCTION

The explosion of student data and rapid advancement in learning technology are completely transforming the way universities keep people on track and help them succeed. Researchers now argue that a combination of data types (attendance, LMS use, behavioral interactions) should be combined to create richer and more predictive risk models rather than static scores like GPA or past tests that simply don't paint the full picture of what puts a student at risk [2],[3].

One of the greatest concerns of any university is identifying students who may drop out or fail before it is too late [4]. Behavioral data streams, in fact, are the most effective early warning indicators because they reveal students' learning trajectories and engagement patterns over time [5]. Plus, risk isn't static; it changes with course difficulty or seasonal bumps, so we need assessment systems that can change on the fly. Static models are not able to keep up and tend to miss opportunities for early intervention [3].

To address these challenges, this report describes an Intelligent Student Risk Assessment and Prediction Engine that combines a suite of machine-learning techniques, such as Random Forest and XGBoost, to integrate academic and behavioral data into a single risk profile for each student [7],[8]. The key innovation is a dynamic risk scoring algorithm that automatically adjusts scores by school wide trends and seasonal fluctuations, improving prediction accuracy and relevance [9].

Further, the system employs explainable AI (XAI) tricks to make predictions transparent and interpretable to teachers and admins, establishing trust and facilitating action on the results [10],[11]. Using the live dashboard, stakeholders can easily visualize a student's risk journey, and customize proactive support that aligns with campus objectives.

Altogether, this work is taking our early-warning systems from old-school reactive tools to smart, adaptable predictors. The engine is prepared for responsible, large-scale use following good data-privacy and AI ethics practices, with the goal of improving student retention and academic performance in our increasingly complex learning ecosystems [12].

1.1 Background & Literature Survey

With the explosion of digital educational data and the advancement in machine learning techniques, the field of educational data mining and learning analytics has really blossomed in recent years [1]. This literature review examines what is currently taking place in student risk assessment and prediction systems, highlighting the key developments, the approaches being taken and the emerging trends that inform the development of more intelligent student support systems.

Traditional student risk assessment models relied on static academic indicators and demographic information [2],[3]. In the higher education arena, early warning systems have relied primarily on cumulative grade point average, standardized test scores, and simple demographic data in order to determine at-risk students. But those approaches have been limited because they do not capture the dynamic and complex nature of student risk factors.

The shift to data-driven practice was given an added push by the explosion of learning management systems and digital learning platforms that produce abundant streams of behavioral and engagement data [4]. This transition shifted us from retrospective analysis to predictive modeling, allowing schools to shift from reactive to proactive student support strategies.

Machine learning has recently demonstrated great potential to improve student risk prediction. Ensemble learning techniques such as Random Forest and XGBoost are able to cope with heterogeneous data and improve prediction accuracy over single-classifier models [7],[8]. They can illustrate nonlinear relationships among many features, giving a more comprehensive view of student risk [6].

Ensemble methods have been proven to be better than the classical statistical methods in some educational datasets with an accuracy gain of 15-25% [7]. Silva et al. were able to present that ensemble methods are superior to individual classifiers because they effectively fuse the results of heterogeneous learning algorithms in order to minimize prediction variance and bias [8]. Still, we have to deal with the temporal dynamics and change in student behavior over the course of the semester [9].

Recent literature emphasizes the need to include behavioral data such as LMS participation and interaction patterns that provide timely insights on engagement that precede academic outcomes [3],[4]. The combination of data streams has become an important factor in developing holistic risk assessment models. Multimodal learning analytics combine these heterogeneous streams to provide rich risk profiles for more accurate and timely predictions [8].

Research has shown that learning management system behavioral indicators are able to predict academic outcomes with a longer lead time than the traditional grade-based measures, providing opportunities for earlier intervention [3]. Engagement patterns - such as frequency of student logins, resource usage and online discussion participation - have been found to be good predictors of academic success [4].

Apart from raw predictive performance, new research puts a premium on explainability in AI-based educational tools [9]. Explainable AI (XAI) frameworks can provide transparency to teachers and administrators about the underlying basis of risk predictions to build trust and enable data-driven decision making that is aligned with teaching goals [10]. Model-agnostic techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model Agnostic Explanations) are becoming popular to explain model decisions in education [9].

The desire for model interpretability is not just a technical issue-it crosses the border into the ethical and pedagogical domain, where automated decision-making should complement, not replace, human judgment and be educational values-oriented [10].

Student risk is a dynamic quantity, affected by temporally and institutionally induced factors such as academic calendar events, course difficulty and changing student circumstances [7],[12]. Static models tend to overlook these dynamics and result in late or missing alerts [2]. Emerging research advocates for adaptive risk scoring systems that continuously update risk estimates in real time to reflect constantly changing campus patterns and student behavior [12],[13].

The recent advances in real-time adaptive modeling are promising for continuous, risk adaptation based assessment to accommodate seasonal patterns of courses, course details, and individual student trajectories [13]. These systems are a significant advance over traditional batch-processing systems that provide only periodic updates, instead of continuous monitoring.

1.2 Research Gap

There has been a lot of work done to fairly accurately predict which students are at risk, but there are still enough gaps that prevent the current approaches from being super effective and useful. Most of the standard models are based mainly on static academic cues (such as previous grades or test scores), and do not incorporate the rich behavioral data or the timing information that characterize the true complexity of at-risk behaviors [2],[3]. Plus, many of the techniques available use only a single machine learning model, and thus lack the additional resilience and accuracy gained from ensembles [7],[8].

A gaping hole in a lot of today's research is that it almost entirely fails to address adaptive or real-time risk scoring. Static risk scores are unable to adapt to changes that occur as a result of school events, academic calendar fluctuations, or simply a student's personal life, leading to late or inaccurate risk notifications [3],[6]. Also, because many of the predictions obscure what's going on under the hood, educators can't trust them, and it's a tough sell to get them on board, as teachers need clear and transparent insights to guide interventions [10],[11].

On the other hand, this new Intelligent Student Risk Assessment and Prediction Engine comes along with a bouquet of new ideas to fill the gaps. It draws together various kinds of academic and behavioral data in order to create a comprehensive risk profile for each student [2],[4],[5]. Using ensemble methods such as Random Forest and XGBoost improves the accuracy and maintains the power of the model [7],[8]. Dynamic risk scoring system updates as needed to reflect timing and school situation changes, and provides you with relevant, timely notification [9],[12],[13]. Finally, connectible explainable AI means that how the model arrives at its decision is actually visible, which instills confidence and allows lecturers and admin staff to operationalize it [10],[11].

Feature	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	**Our Proposed Method**
Multimodal Data Integration	✗	✗	✗	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
LMS Engagement Data	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Behavioral Data Streams	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
Ensemble Learning Methods	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✓
Dynamic Risk Scoring	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓	✓
Real-time Prediction	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓
Temporal/Seasonal Adaptability	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓
Explainable AI Implementation	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓	✗	✗	✓
Privacy-Preserving Analytics	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓
GDPR Compliance	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓

Interactive Dashboard	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Stakeholder-Centric Design	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Proactive Intervention Support	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✓

Table 1 Comparison between Existing Research Methods and Proposing Method

1.3 Research Problem

In fact, educational data science is all about how to anticipate the performance of students and when and how teachers should intervene on their behalf [1]. Most schools still use simple dashboards which only provide test scores and attendance, then feed that data to ML engines that are sealed black boxes. Since those models fail to elucidate how they come to a conclusion, teachers who want a strong rationale for every recommendation end up completely ignoring the predictions [1].

Enter explainable AI tools like SHAP and LIME that attempt to solve the transparency problem by introducing a new layer on top of individual and overall outputs, transforming otherwise inscrutable algorithms into narratives we can actually comprehend [2],[6]. Yet, bringing those stories into real-world classrooms is challenging algorithms have the tendency to behave arbitrarily, data variables are often entangled in each other, and each of the explanations requires a touch of pedagogy to be comprehensible [2],[4].

This is made worse when schools use a single source of data. Adding login log, click patterns, mood survey, and other signals can improve early warning accuracy by about 30% [3],[5]. Yet many schools turn a blind eye to this and continue to obsess over flashy dashboards rather than the messy data that could aid struggling students earlier [3],[5].

Whilst the concept of multi-modal learning analytics (MMLA) is an exciting one, most higher education institutions still face challenges in capturing, connecting and utilizing those diverse data sources whilst complying with stringent privacy regulations, such as GDPR [3],[7]. On top of that, existing prediction tools tend to overlook the ebb and flow of campus life - such as exam week panic - and so are not reliable enough, leaving staffers without warning in times when prompt assistance is most valuable [8]. Worse, when models warn of risk, they rarely provide concrete actionable steps for teachers to take or timely and relatable warnings that students and parents can actually understand [1],[2].

This paper addresses those related issues, by constructing a flexible, explainable, and secure AI system. Our method combines ensemble with SHAP/LIME and federated learning, making predictions interpretable. Interventions can be effected ad hoc and personal data never leaves the school [2],[3],[7]. By linking the latest technology to actual classroom needs, we strive to provide teachers with sound, practical advice that will increase student achievement without sacrificing privacy or legal responsibility [1],[7].

2. OBJECTIVES

2.1 Main Objective

The main objective of this research is to develop an Intelligent Student Risk Assessment and Prediction Engine that leverages advanced ensemble machine learning techniques and multimodal educational data to accurately and dynamically predict students at risk of academic failure or dropout. This engine aims to transform traditional early warning systems by introducing adaptability to real-time institutional and seasonal changes and by providing explainable, actionable insights to educators and administrators, ultimately enabling timely and effective interventions to improve student retention and academic success.

2.2 Specific Objectives

- **Collect and Integrate Multimodal Student Data:**

Gather comprehensive academic, behavioral, and engagement data from diverse sources such as grade records, attendance logs, and learning management systems to build a rich dataset representing multiple aspects of student activity and performance.

- **Design and implement ensemble machine learning models**
  Improve prediction accuracy and robustness over traditional single-model approaches using suitable ensemble algorithms like Random Forest and XGBoost.

- **Develop an Interactive Dashboard for Stakeholder Engagement**
  Build a user-friendly interface for visualizing risk scores and trends, promoting actionable insights and facilitating effective communication between educators, advisors, and institutional decision-makers.

- **Validate the Proposed Engine Using Historical and Real-Time Data**
  Perform rigorous statistical validation and backtesting on historical student cohorts, along with pilot testing in real educational settings, to ensure the model's predictive performance, scalability, and practical utility.

- **Ensure Compliance with Ethical and Privacy Standards**
  Incorporate data governance frameworks and adhere to regulatory requirements such as GDPR to safeguard student privacy and promote responsible use of AI in educational analytics.

3. METHODOLOGY

3.1 Technologies

The development of the Intelligent Student Risk Assessment and Prediction Engine requires a robust, scalable, and flexible technology stack that covers all system layers from data ingestion to user interaction and visualization. The choice of technology will be finalized after thorough testing and benchmarking; however, based on contemporary standards and best practices, the following technology categories and options are under consideration:

Frontend Technologies

- **Frameworks:** React.js, Angular, or Vue.js are potential candidates owing to their ability to build responsive, dynamic, and user-friendly interfaces. These frameworks support real-time updates and seamless interaction with backend APIs, which is essential for visualizing student risk scores and trends.

- **Data Visualization:** Libraries like D3.js or Chart.js will be evaluated to create interactive and insightful graphical displays of student risk metrics, enabling educators to easily interpret data and take informed actions.

Backend Technologies

- **Programming Languages and Frameworks:** Python (with Flask or FastAPI) or Node.js (using Express.js) will be tested for backend service development. Python offers extensive machine learning and data processing libraries, while Node.js excels in handling asynchronous API requests efficiently.

- **Machine Learning Libraries:** Scikit-learn, XGBoost, and TensorFlow/PyTorch will be explored for developing ensemble learning models (Random Forest, Gradient Boosting) and dynamic risk scoring algorithms, optimizing prediction accuracy and computational efficiency.

Databases and Data Storage

- **NoSQL Databases:** MongoDB, Firebase or Cassandra may be chosen for storing unstructured or semi-structured data like behavioral logs, LMS activity, and real-time streaming data.

- **Cloud Storage & Services:** Cloud platforms such as AWS, Azure, or Google Cloud that offer scalable object storage (e.g., S3, Blob Storage) and managed database solutions, ensuring flexibility and scalability.

APIs and Middleware

- **RESTful APIs:** Flask, FastAPI, or Express.js frameworks will be used to create secure and efficient RESTful APIs that expose model predictions, risk scores, and explainability outputs to client applications.

- **Authentication & Security:** OAuth 2.0, JWT (JSON Web Tokens), and HTTPS will be incorporated to ensure secure data access and transfer, complying with data privacy regulations.

- **API Testing:** Tools like Postman, widely used for designing, testing, and automating RESTful APIs. It supports automation, collaboration, version control, and integration with CI/CD pipelines.

These technologies will be critically evaluated during the implementation phase, with selection based on factors such as prediction accuracy, model interpretability, processing speed, scalability, ease of integration, security, and user experience. This approach ensures end-to-end system reliability from raw data ingestion to actionable educator insights across varying deployment environments.

3.2 System Overview Diagram

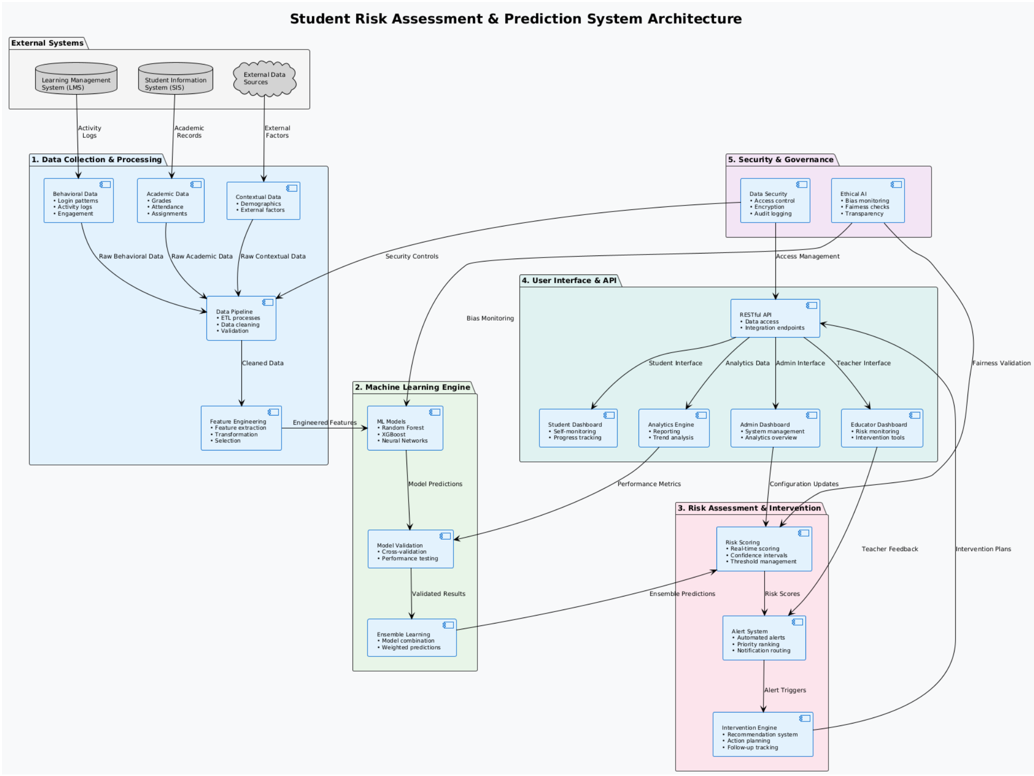

Figure 1 System Overview Diagram

3.3 Component Diagram

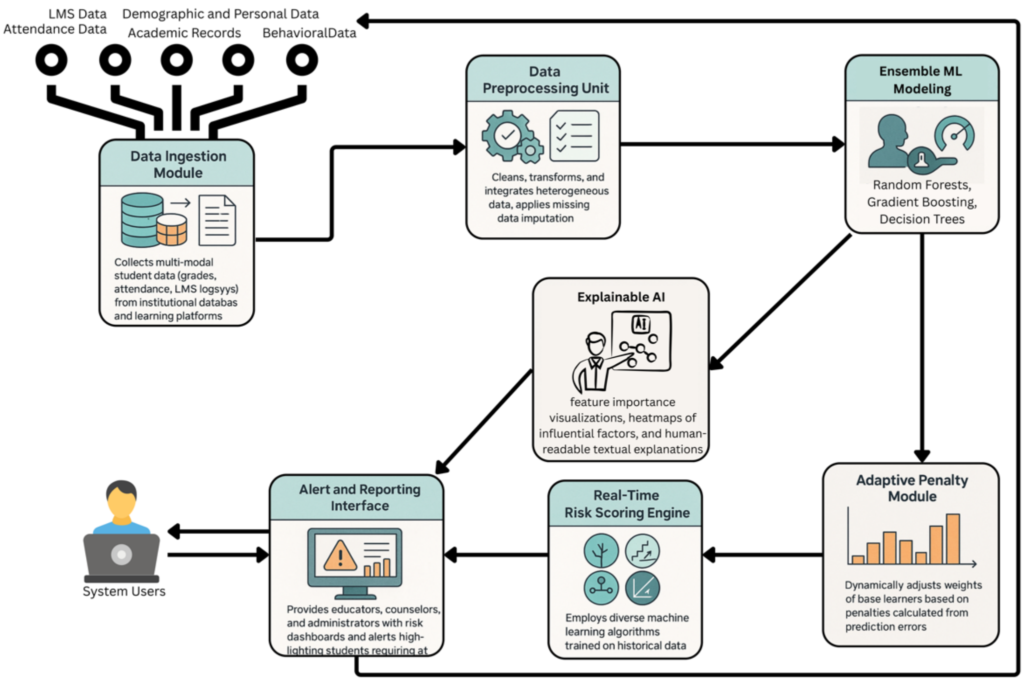

Figure 2 Component Diagram

3.4 Work Breakdown Structure

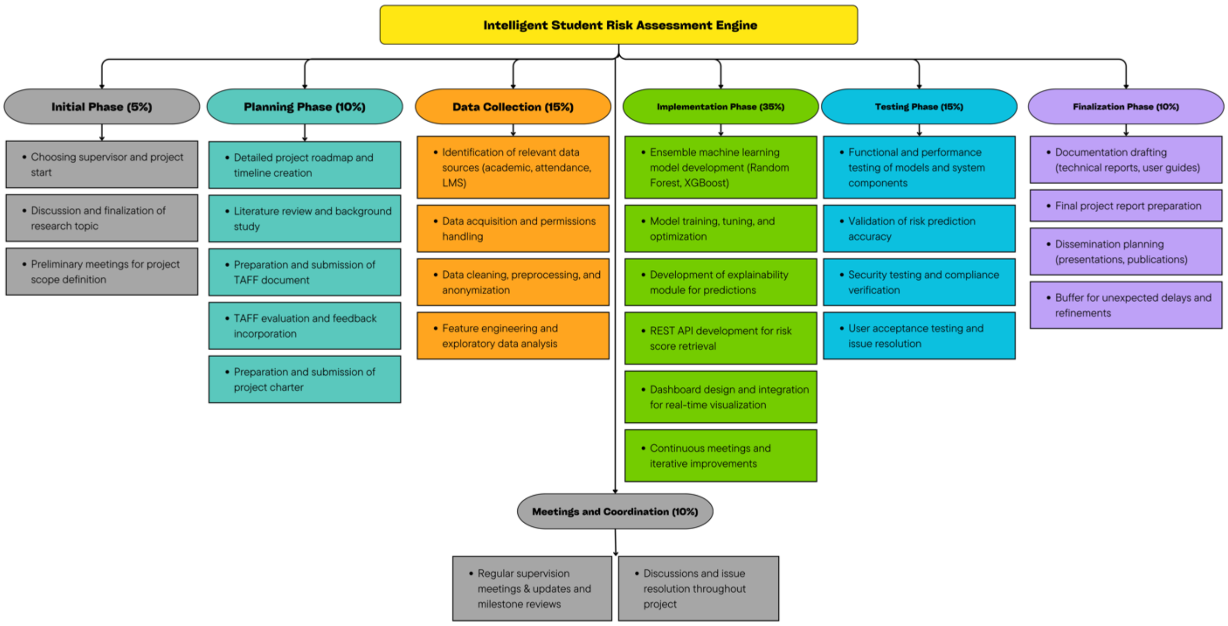

Figure 3 Work Breakdown Structure

4. PROJECT REQUIREMENTS

4.1 Functional Requirements

- Data Integration: The system should be able to collect and integrate student academic records, attendance data, social data and LMS engagement logs from multiple sources in real time or batch mode.
- Data Preprocessing: The system should be able to clean, normalize, and transform raw input data, handling missing or inconsistent entries before analysis.
- Risk Prediction: The system should have capability to predict the risk level of students accurately using ensemble machine learning algorithms (Random Forest, XGBoost).
- Dynamic Risk Scoring: The system should continuously update student risk predictions based on newly received data and evolving academic or institutional conditions.

- API Access: The system should offer secure RESTful APIs to deliver risk scores and explanations to external applications or dashboards.
- Interactive Dashboards: The system should output a user-friendly dashboard that visualizes student risk trends and highlights actionable insights for educators and advisors.
- User Authentication and Authorization: The system should ensure that only authorized personnel can access sensitive student data and prediction results.
- Data Privacy Compliance: The system shall comply with relevant data privacy regulations (e.g., GDPR) to protect student information.

4.2 Non-Functional Requirements

- Performance: The system shall provide risk predictions with latency low enough for near real-time decision support.
- Scalability: The system shall scale to handle large volumes of student data across multiple institutions without degradation in performance.
- Reliability and Availability: The system shall guarantee high availability (uptime of 99.9%) and robust error handling to avoid data loss or downtime.
- Security: The system shall implement encryption for data in transit and at rest, and enforce strong authentication mechanisms.
- Usability:
- The dashboard and API interfaces shall be intuitive, accessible, and support responsive design for various devices.
- Maintainability: The system shall be modular and documented to facilitate timely updates, debugging, and feature additions.
- Explainability: Model explanations shall be comprehensible to non-technical users, ensuring trust in risk assessments.

4.3 Expected Test Cases

Test Case ID	Description	Expected Outcome
TC-FR-01	Data ingestion from multiple sources	Data collected and stored correctly
TC-FR-02	Handling of missing or corrupt data during preprocessing	System cleans or flags malformed data
TC-FR-03	Risk prediction generation with ensemble models	Accurate risk scores produced within time
TC-FR-04	Dynamic risk score updates on new data input	Risk scores refresh reflecting updated status
TC-FR-05	Interpretability of risk predictions	Clear explanations generated per prediction
TC-FR-06	REST API returns correct risk scores and explanations	API responds with valid JSON responses
TC-FR-07	Dashboard visualization of real-time risk data	Risk visualizations display correctly
TC-NFR-01	System response time under typical load	Responses within defined latency threshold
TC-NFR-02	Security test: unauthorized access attempt	Access denied and logged
TC-NFR-03	System scalability test with increased data volume	Stable performance maintained
TC-NFR-04	Compliance with data privacy regulations	Data stored and processed according to policies

Table 2 Expected Test Cases

5. DESCRIPTION OF PERSONAL AND FACILITIES

Registration Number	Name	Description
IT22354792	Ravisanka U.V.P	I am the principal researcher and developer responsible for the design, implementation, and evaluation of the Intelligent Student Risk Assessment Engine. I bring expertise in information technology, data science, and machine learning, which are essential for developing predictive analytics models and building scalable software systems. My background ensures a strong foundation in both the technical and academic understanding necessary for this project. 1. Computing resources that have access to a high-performance personal workstation equipped with the latest processors, ample RAM, and GPU capabilities suitable for training ensemble machine learning models such as Random Forest and XGBoost efficiently. 2. Software and development tools that licensed or open-source access to development environments. 3. Authorized access to anonymized academic datasets, attendance records, and LMS engagement logs as permitted by institutional data-sharing agreements. 4. Network and Cloud Infrastructure

		5. A dedicated, quiet workspace conducive to focused research activities, with facilities for remote collaboration, video conferencing, and regular meetings with supervisors or domain experts. 6. Availability of software for documentation, project management, and report generation to maintain comprehensive logs and status updates throughout the project lifecycle.

Table 3 Description of Personal And Facilities

6. BUDGET AND BUDGET JUSTIFICATION

6.1 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

6.2 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.

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8. APPENDICES

8.1 Gantt Chart

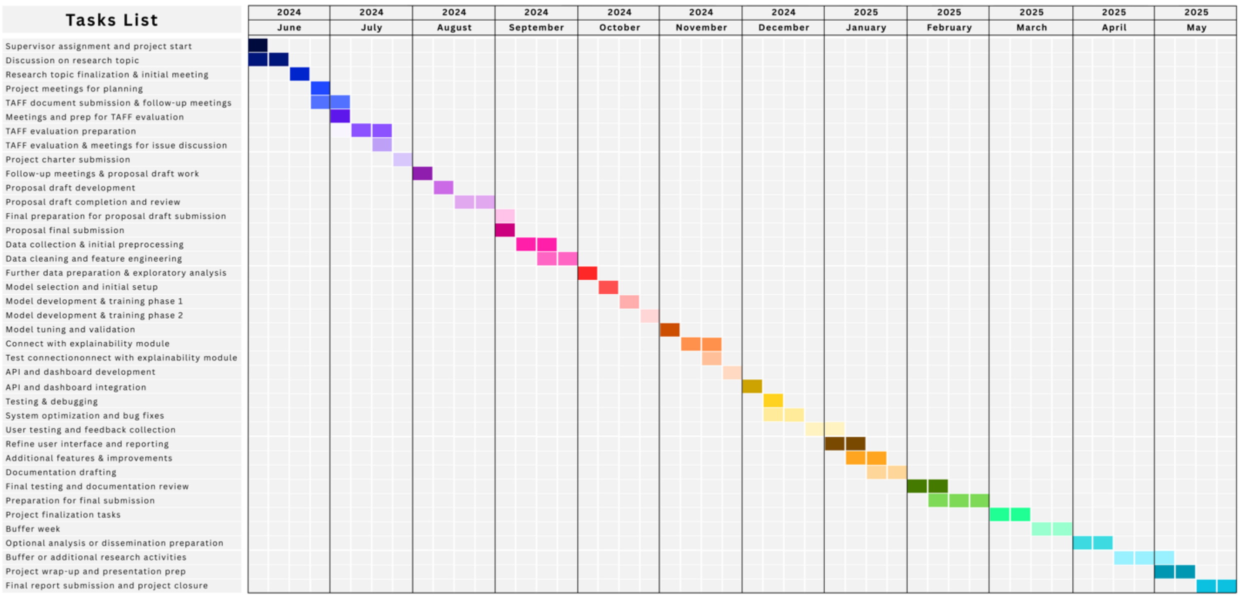

Figure 4 Project Gantt Chart

8.2 Turnitin Report

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Figure 5 Turnitin Report

8.3 Sample UI Designs

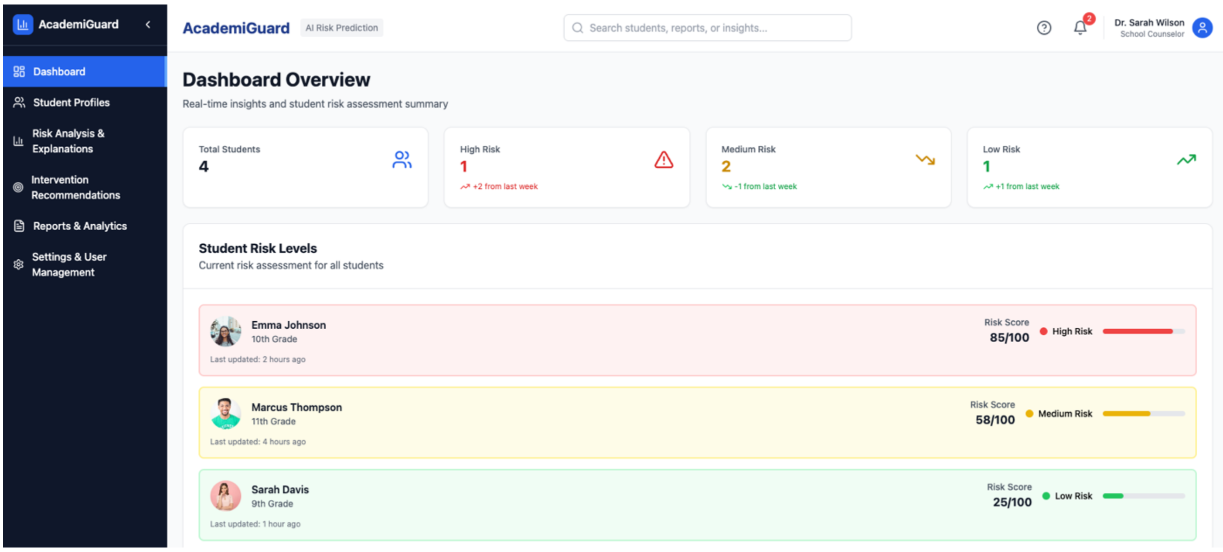

Figure 6 Sample UI 01

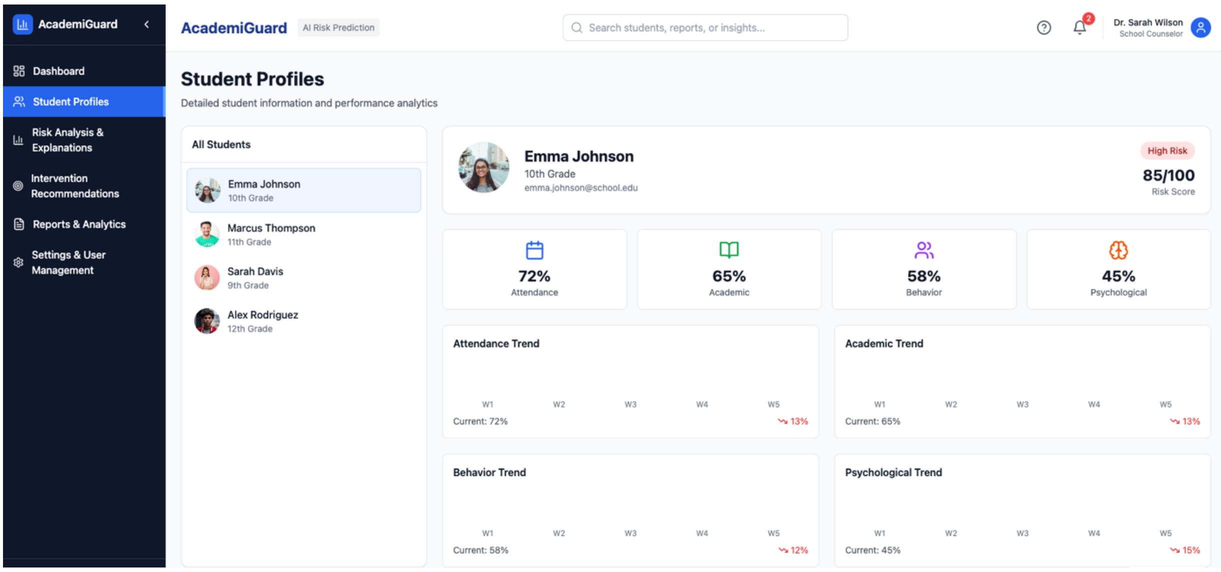

Figure 7 Sample UI 02

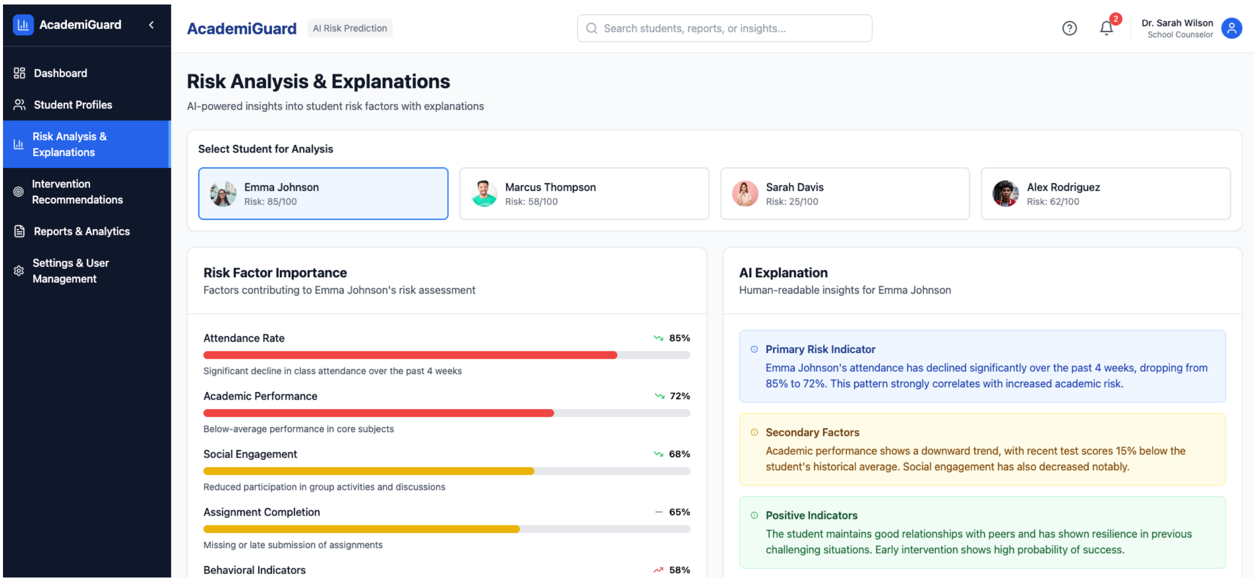

Figure 8 Sample UI 03

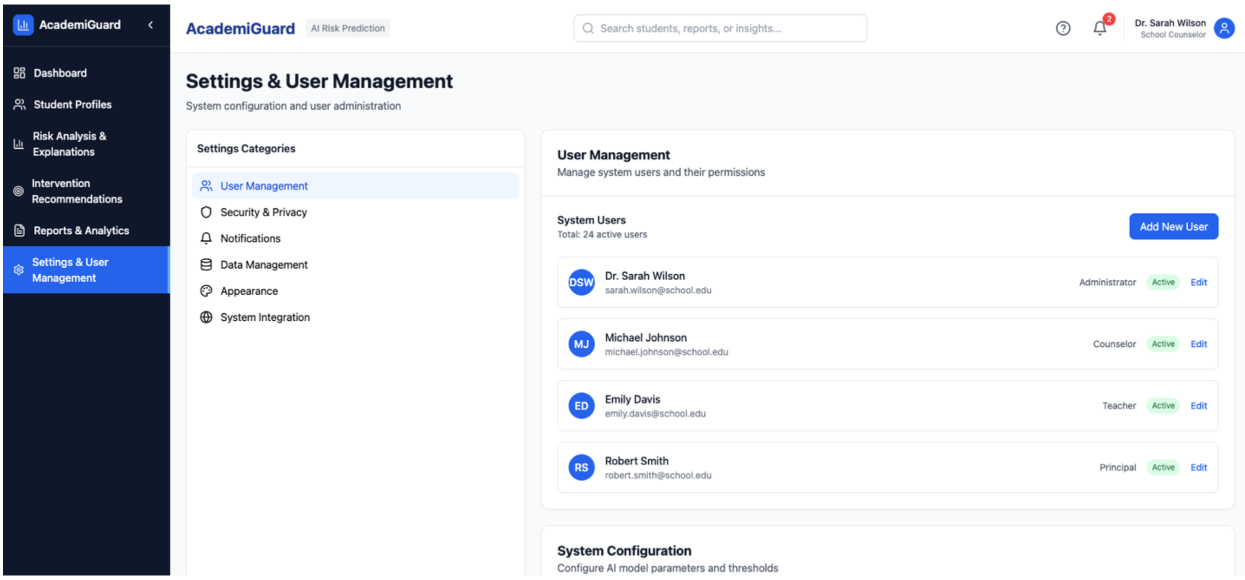

Figure 9 Sample UI 04