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

25-26J-172

Project Proposal Report

Perera I.A.T.D

(Ravisanka U.V.P, Disanayaka S.T, Nimanji D.L.K)

B.Sc. (Hons) Degree in Information Technology

Department of information technology

Sri Lanka Institute of Information Technology

Sri Lanka

August 2025

STUDENT DISENGAGEMENT DETECTION AND PERSONALIZED SUPPORT SYSTEM FOR RE-ENGAGEMENT AND REDUCING DROPOUT RISK

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 page of the candidate & supervisor

We 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
Perera I.A.T.D	IT22902702	

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

29.08.2025

……………………………. ……………………………

Signature of the supervisor Date

Abstract

Student disengagement and dropout remain persistent challenges in higher education, often starting with subtle behavioral changes such as irregular logins, shorter study sessions, or declining responses to system alerts. Early detection and timely adaptive support are crucial to lowering dropout risk and fostering stronger academic continuity.

This research proposes a web-based student performance prediction and early intervention system that combines a Disengagement Detection Model and a Reinforcement Learning (RL) Model to deliver predictive risk detection and dynamic re-engagement strategies. The Disengagement Model, developed using sequential machine learning techniques such as Gated Recurrent Units (GRU), analyzes behavioral patterns such as login frequency, session duration, inactivity gaps, task completion trends, and declining alert interactions to detect early warning signs and estimate future dropout risk. Once a student is flagged, the RL Model intelligently selects the most suitable intervention strategy by choosing the best communication channel (in-app message, email, or SMS), timing (morning, evening, or weekend), and tone while limiting frequency to avoid alert fatigue.

Unlike conventional systems that stop at generic reminders, this approach integrates a feedback-driven support loop. When a student responds, the system collects their feedback through short surveys and sentiment analysis on any messages they send. These insights help identify their blockers such as time pressure, motivation loss, stress, technical issues, or personal difficulties, along with their current emotional state. Based on this, the system delivers pre-set supportive templates such as motivational nudges, simple micro-planning prompts, stress-reduction reminders, or helpdesk contact messages. If strong signs of stress or personal struggles are detected, the system bypasses further automation and escalates the case to human support.

If students remain unresponsive to automated interventions, a social engagement layer is activated. Selected peers, either chosen by the student or drawn from their group activity teammates, are notified that their friend seems disengaged. With the student's consent, these peers can send encouraging one-click messages or short personal notes, which appear as friendly chats rather than system alerts. This peer-driven support helps reintroduce a sense of belonging and can continue as casual in-app or external chats, offering a human touch before escalating to formal staff intervention.

Students who still do not respond are referred to human mentors or advisors through a dedicated staff dashboard containing their engagement history, sentiment logs, and suggested outreach scripts. Re-engagement is measured not just by immediate logins but by sustained improvement over several weeks, ensuring genuine recovery rather than temporary spikes in activity.

Table of Content

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Abbreviation	Description
ML	Machine Learning
API	Application Programming Interface
RL	Reinforcement Learning
GRU	Gated Recurrent Unit
SMS	Short Message Service

1. INTRODUCTION

Student dropout and low academic engagement remain persistent challenges in higher education institutions worldwide. Many students begin their academic programs with enthusiasm but gradually lose interest or fall behind due to factors such as poor time management, low motivation, difficulties with coursework, or personal and technical issues. Research has shown that disengagement often begins as a slow drift, marked by subtle behavioral patterns, long before a student formally drops out. These patterns include reduced logins to the learning platform, shorter study sessions, ignoring system alerts, and frequent last-minute submissions. Detecting these early signs provides a critical window for institutions to step in with timely support before students reach the point of no return.

Traditional student support systems mainly focus on academic outcomes such as test scores and grades to identify at-risk students. However, this approach reacts only after performance has already declined. Modern educational technologies are shifting from this reactive mindset to a proactive one, emphasizing early detection and preventive engagement. By analyzing real-time behavioral data, such systems can detect risks early and intervene before disengagement becomes severe. This shift opens new opportunities for educational institutions to prevent, rather than simply respond to, dropouts.

This research proposes a web-based student performance prediction and early intervention system designed around this proactive philosophy. The system integrates two core models: a Disengagement Detection Model and a Reinforcement Learning (RL) Model. The Disengagement Model may use sequential machine learning techniques such as recurrent neural networks to analyze behavioral activity data including login frequency, session duration, alert interactions, and task completion patterns to predict which students are likely to disengage. Once students are flagged, the RL Model dynamically determines how and when to intervene. Unlike static predictive models, the RL component can learn continuously from live interaction data, exploring different combinations of communication channel (in-app message, email, or SMS), timing (morning, evening, weekend), and tone, and receiving feedback rewards based on outcomes such as survey responses, logins within 24 hours, or session completions.

Importantly, the system does not stop sending reminders. When students begin responding, it collects quick feedback through short in-app surveys and sentiment analysis on any messages they send. These insights are used to identify their primary blockers, such as time pressure, low motivation, stress, technical difficulties, or personal challenges, as well as their current emotional state. Based on these results, the system delivers pre-set supportive templates such as motivational nudges, micro-planning prompts, stress-reduction reminders, or helpdesk contact messages. If strong signs of stress or personal difficulties are detected, the system bypasses further automation and escalates the case directly to human support staff.

If students continue ignoring system interventions, a social engagement layer is activated as a final automated step before human escalation. Selected peers, either chosen by the student or drawn from their group activity teammates, are notified that their friend appears to be disengaged. With the student's prior consent, these peers can send encouraging one-click messages or short personal notes that appear as friendly chats rather than system alerts. This peer-driven support provides a sense of belonging and can spark renewed motivation in a natural, non-intrusive way.

For students who remain inactive despite these steps, the system escalates their case to academic staff through a dedicated dashboard. Staff can view their recent activity history, sentiment trends, and receive suggested outreach scripts to personally guide the student. Finally, the system tracks not only quick returns but also sustained re-engagement, marking students as fully re-engaged only after they maintain consistent activity over multiple weeks.

By combining early risk detection, controlled adaptive interventions, emotion-aware feedback, peer-powered social motivation, and human-in-the-loop escalation, this research introduces a practical and human-centered framework for reducing student dropout. The proposed system aims not only to identify disengaged students but also to actively support them in regaining momentum, ultimately fostering long-term engagement and stronger academic outcomes.

1.1 Background and literature survey

Student engagement is widely recognized as a strong predictor of academic success in higher education. Early warning signs of disengagement, such as fewer logins, shorter study sessions, ignored alerts, and last-minute submissions, often appear weeks before grades decline, creating a critical window for preventive support. This has driven a shift in learning analytics from retrospective, grade-based flags to proactive early-warning systems that use behavioral traces from Learning Management Systems (LMS) to detect risk earlier and enable timely outreach.

Early campus-scale work at Purdue (Course Signals) demonstrated the potential of this approach by combining performance, demographic, and engagement data to generate traffic-light risk indicators that prompted instructor action, resulting in improved feedback loops and student behaviors [1]. Building on this, the Open Academic Analytics Initiative (OAAI) operationalized predictive models in a portable pipeline, cleaning LMS data, training risk models, and feeding alerts into advisor workflows to show how predictive analytics can be made actionable rather than purely descriptive [2].

At the massive open online course (MOOC) scale, researchers shifted from treating all learners alike to modeling engagement trajectories over time. Kizilcec, Piech, and Schneider clustered longitudinal activity patterns to reveal behavioral subpopulations such as completers, auditors, and disengages, highlighting that students follow distinct pathways and benefit from tailored interventions rather than uniform nudges [3]. Emotional state has also emerged as an important predictor. Wen, Yang, and Rosé showed that sentiment expressed in discussion forums correlates with dropout risk, suggesting that lightweight emotion signals can enrich behavioral models when text data is available [4].

Several studies have demonstrated that dropouts can be predicted reliably using behavioral features. At MITx, Taylor, Veeramachaneni, and O'Reilly engineered fine-grained clickstream features to achieve high short-horizon predictive accuracy, illustrating the value of detailed activity traces for timely early warnings [5]. Whitehill and colleagues extended this work by emphasizing that prediction alone is insufficient and argued for systems that respond automatically and quickly with targeted interventions such as dynamic surveys to capture blockers before students disappear [6]. Similarly, Bañeres et al. highlighted that reducing the delay between detection and response is crucial because alerts that arrive too late are ineffective even if model accuracy is high [7].

Recent work has also pointed to the importance of social belonging and emotional motivation in preventing dropout. Brooks, Carroll, and Giles found that structured social belonging interventions can significantly improve retention in online courses, showing that peer support and community-building can complement automated systems [9]. In parallel, Liu, Chen, and Wang surveyed reinforcement learning approaches for personalized education and showed how RL can adapt outreach strategies over time based on feedback, making interventions more responsive and less repetitive [10].

Synthesis. Across campus and MOOC contexts, the literature shows that disengagement can be predicted from routine LMS traces, engagement patterns are heterogeneous and benefit from segmentation, affective signals can enhance behavioral models, timely follow-up is critical, and social belonging can help sustain engagement. These insights inform our approach of combining a Disengagement Detection Model for early detection, a reinforcement learning engine to optimize the timing and channel of interventions, lightweight surveys and sentiment analysis to understand blockers, and a peer-driven social layer with structured escalation to staff. This design aims to close the gap between risk prediction and actual re-engagement support.

1.2 Research Gap

The literature review shows that significant progress has been made in developing early-warning systems and student dropout prediction models. Studies have demonstrated that disengagement can be detected using LMS behavioral traces, predictive analytics, and even sentiment cues from student discussions [1][4]. These works confirm that risk can be identified well before it appears in grades. However, several critical gaps remain that reduce the practical impact of such systems.

First, most existing systems focus primarily on prediction rather than intervention. They flag at-risk students but provide little guidance or structured follow-up to help those students re-engage [1][3]. This limits their real-world effect because early alerts alone do not reverse disengagement.

Second, while some studies have used sentiment analysis to detect student emotions [4], these methods depend heavily on large text datasets such as forum posts, which are not always available. Lightweight, scalable approaches such as quick in-app micro-surveys and sentiment analysis on short student replies have been largely overlooked.

Third, very few systems apply Reinforcement Learning (RL) to personalize engagement recovery. RL has shown promise in adaptive tutoring and educational recommendations, but its use for dynamically deciding when and how to intervene (choosing optimal timing, channel, and tone) remains underexplored [5][10].

Fourth, none of the reviewed systems include social engagement mechanisms such as peer cheering. Research has shown that social belonging can significantly increase student retention [9], yet prior systems do not use social pull-in strategies where selected peers are invited to send supportive messages if a disengaged student continues ignoring system interventions.

Fifth, most systems also lack a human-in-the-loop escalation pathway. Sensitive or serious cases often require staff involvement, but existing tools do not route high-risk students to academic advisors with activity timelines, sentiment trends, and suggested outreach scripts [7].

Finally, prior work rarely focused on sustained recovery. Many studies track only short-term logins after alerts rather than checking if students genuinely re-engage and maintain consistent activity over multiple weeks.

Technologies & Methods	Research Paper [1]	Research Paper [2]	Research Paper [3]	Research Paper [4]	Research Paper [5]	Proposed Research
LMS Data for Early Detection	✓	✓	✓	✓	✓	✓
Predictive Modeling (ML)	✓	✓	✓	✓	✓	✓
Sentiment / Emotion Analysis	✗	✗	✗	✓	✗	✓
Reinforcement Learning (RL)	✗	✗	✗	✗	✗	✓
Personalized Guidance	✗	✗	✗	✗	✗	✓
Social Engagement (Peer Cheers)	✗	✗	✗	✗	✗	✓
Human-in-the-loop Escalation	✗	✗	✗	✗	✗	✓

Table 1.1.Comparison of the existing research methods and proposed method

1.3 Research problem

Despite significant advances in early-warning systems and predictive analytics for education, several critical challenges remain unresolved. Existing research has shown that it is possible to use LMS behavioral data to identify disengaged or at-risk students with reasonable accuracy [1]-[5]. However, most of these systems stop at the point of detection, providing risk flags or alerts but not offering a structured path for re-engagement. As a result, students who are identified as at risk often receive little more than a warning, without clear guidance or support to help them recover and continue their learning journey.

Another key issue is the lack of adaptiveness in current intervention methods. Many institutions still rely on static reminders, such as generic emails or scheduled notifications sent at fixed times through limited channels. These approaches often become repetitive, easy to ignore, and ultimately ineffective. While Reinforcement Learning (RL) has shown promise in optimizing decisions and personalizing recommendations in other domains, it has rarely been applied to student engagement recovery [10]. Without adaptiveness, interventions cannot adjust dynamically to differences in student behavior, timing preferences, or channel responsiveness, which limits their effectiveness.

A further gap lies in how student emotions and personal barriers are considered. While some studies have experimented with sentiment analysis of large text datasets [4], such methods are not always practical or available in every educational setting. Lightweight and student-friendly mechanisms, such as short in-app surveys to quickly capture blockers (time constraints, low motivation, content difficulty, technical issues) and mood levels, combined with sentiment analysis of short student replies, have not been fully explored in engagement recovery systems. Without understanding students' emotional states, interventions risk overlooking the human side of disengagement.

Another missing element is social support. Research shows that social belonging and peer encouragement can significantly reduce dropout [9], yet current systems rarely include mechanisms for peers to support disengaged students. Features like peer cheers quick, supportive messages from close teammates could help reignite motivation through positive social connection, especially if activated when students ignore system interventions, but such mechanisms are absent from prior models.

Finally, there is limited integration of human-in-the-loop escalation. Fully automated systems cannot handle every situation, especially when students face severe emotional or academic challenges. Current models rarely provide structured workflows to route serious cases to academic staff, advisors, or mentors through dashboards with student timelines, sentiment trends, and suggested outreach scripts [7]. This creates a critical gap between automated detection and meaningful human support.

Therefore, the core research problem can be summarized as follows: There is a lack of a comprehensive system that not only detects disengaged students early but also delivers adaptive (RL-driven), survey-based, sentiment-aware, and socially supported interventions, while ensuring that serious cases are escalated to academic staff for timely follow-up and that recovery is tracked until sustained engagement is achieved.

This problem highlights the need for a solution that closes the loop from early detection to adaptive interventions, to social motivation, and finally to human support, ensuring that at-risk students are not just identified but actively supported back into meaningful and lasting engagement.

2. OBJECTIVE

2.1Main objective

The main objective of this research is to design and develop a web-based student performance prediction and early intervention system that not only identifies students at risk of disengagement but also actively supports them back into meaningful and sustained engagement.

Unlike existing systems that stop at prediction, the proposed solution aims to build a closed-loop framework that combines early risk detection, adaptive interventions, emotion-aware feedback, peer-based social support, and human follow-up. It will deliver timely guidance based on students' behavioral patterns, emotional signals, and engagement trends, while escalating serious or persistent cases to academic staff when needed.

The overall goal is to reduce student dropout by ensuring that learners who show early signs of disengagement are not just flagged but re-engaged through adaptive support, social encouragement, and sustained recovery tracking.

2.2 Specific objectives

1. To detect early signs of disengagement by analyzing student activity patterns (such as logins, session duration, task completion, and interaction drops) and classifying students based on their risk levels.
2. To deliver adaptive interventions by selecting the most suitable timing, channel, and tone for each student, using a reinforcement learning approach that learns from students' response patterns and behavior history.
3. To capture students' blockers and emotional state through brief in-app surveys and sentiment analysis on short student replies, enabling the system to understand challenges such as time constraints, low motivation, stress, or technical issues.

4. To provide supportive re-engagement guidance using pre-set message templates such as motivational prompts, micro-planning reminders, stress reduction tips, and helpdesk contact information.
5. To activate a social engagement layer when students ignore system interventions, allowing selected peers to send supportive peer cheer messages to re-ignite motivation and provide a sense of social belonging.
6. To establish a human-in-the-loop escalation process where high-risk students are flagged on a dedicated dashboard with their activity history, sentiment trends, and suggested outreach actions for academic staff.

3. METHODOLOGY

3.1 Technologies

The proposed system will be developed as a web-based platform, integrating backend machine learning components and frontend user interfaces to support students, peers, and academic staff. A combination of reliable, scalable, and widely adopted technologies will be employed to ensure feasibility, maintainability, and real-time responsiveness.

Backend Development- The backend will be developed using a suitable web framework such as Spring Boot or Node.js. It will handle the core system logic, integrate machine learning models, and manage communication between components through RESTful APIs.

Database and Data Storage- A secure cloud-based database will be used to store student activity data, engagement history, sentiment logs, survey responses, and escalation records. Firebase will support real-time data synchronization and push notifications to ensure students receive alerts and staff receive updates instantly.

Machine Learning Components-The machine learning environment will be developed in Python.
It will include:

- **Disengagement Detection Model:**
  This model will analyze student behavioral data such as login frequency, study session duration, task completion rates, alert responses, and engagement trends. A rule-based baseline may be implemented initially for transparency. If sequential behavioral data is available, traditional classifiers (e.g., Logistic Regression, Decision Trees, Random Forest, Gradient Boosted Models) and optionally recurrent models (e.g., GRU) may be explored to capture temporal patterns. The output will classify students into engagement levels such as Normal, Watchlist, or At-Risk.

- **Reinforcement Learning (RL) Intervention Model:**
  This model will dynamically select the most suitable timing, channel, and tone for delivering interventions. Q-Learning will be considered as an interpretable baseline, with the option to explore more advanced approaches such as Deep Q-Networks (DQN) if larger datasets are available.
  States will represent student risk level, time of day, prior communication history, and response patterns.
  Actions will include choosing the channel (in-app, SMS, email), timing (morning, afternoon, evening), and tone (short nudge, supportive message).
  Rewards will be based on observed engagement outcomes, such as logins within 24 hours, survey completion, or study sessions of at least 10 minutes.

- **Mood and Sentiment Analysis:**
  To understand students' emotional context, the system will use lightweight self-reported mood scales (1–5) embedded within micro-surveys and apply lexicon-based sentiment analysis on short free-text replies from students. Optionally, third-party sentiment APIs (e.g., Google Cloud Natural Language, AWS Comprehend) may be used for enhanced accuracy.

The results will classify mood states (e.g., Positive, Neutral, Negative) and guide the choice of pre-set guidance templates or trigger escalation if severe stress or personal difficulties are detected.

Guidance Delivery Mechanism-Based on survey and sentiment results, the system will deliver pre-set guidance templates rather than generating educational content. These templates will include motivational nudges, micro-planning prompts, stress reduction reminders, and helpdesk contact information. If the student shows signs of very low mood or serious personal difficulties, automated guidance will stop and the case will be escalated directly to staff.

Peer Social Engagement Layer-If a disengaged student repeatedly ignores system interventions, a social engagement layer will activate. Selected peers, either chosen by the student or identified from their group activity teams, will be invited to send supportive one-click messages or personal notes. These appear as friendly peer messages rather than system alerts, helping to reignite motivation through social belonging. All peer interactions will be logged as feedback for the RL model.

Frontend Development

The user interfaces for students, peers, and staff will be built using a responsive frontend framework such as React.js. The dashboards will present engagement insights, sentiment trends, survey responses, guidance suggestions, peer messages, and escalation alerts in an accessible format.

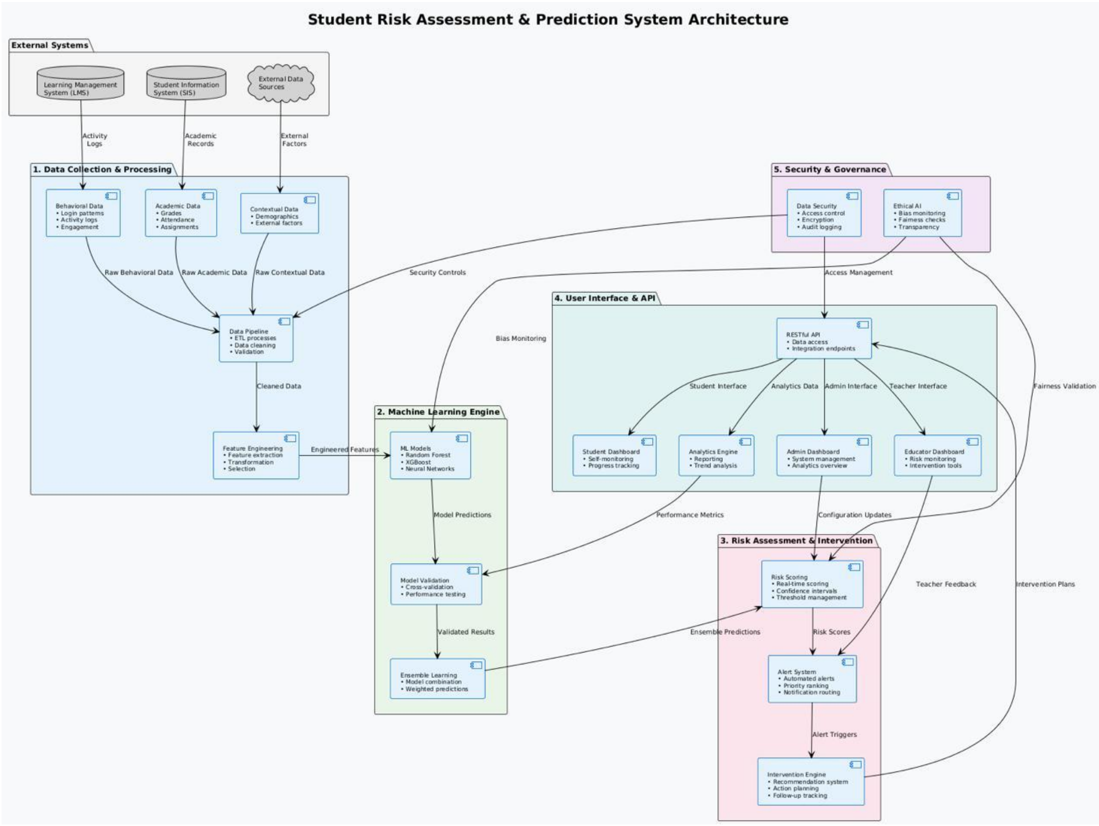
Notification and Communication Services

Firebase Cloud Messaging (FCM) will provide real-time in-app notifications and chat delivery. Integration with SMS and email gateways will support multi-channel communication for students who prefer alternative contact methods.

Hosting and Deployment

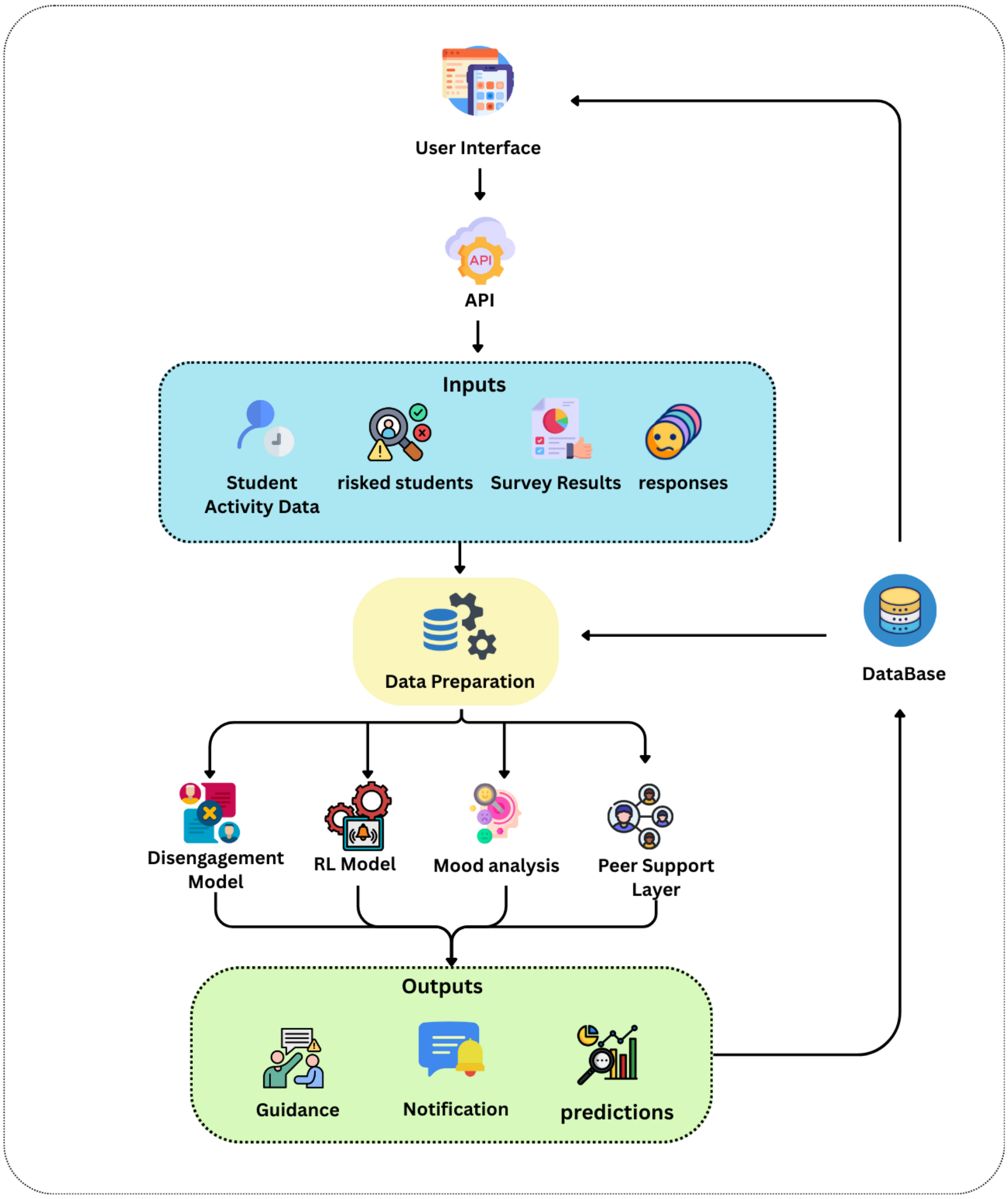
The platform will be deployed on a cloud infrastructure such as Google Cloud or AWS to ensure scalability, data security, and high availability.

3.2 System Architecture



3.1 System Architecture

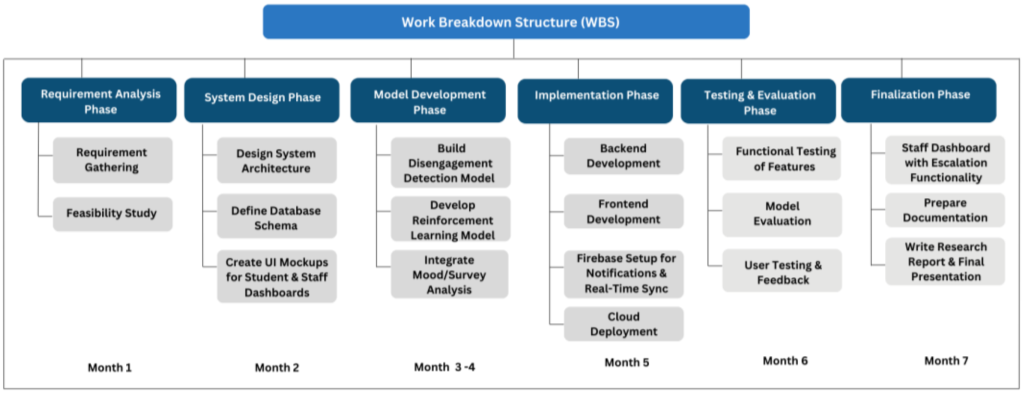
3.3 Component Overview Diagram



\

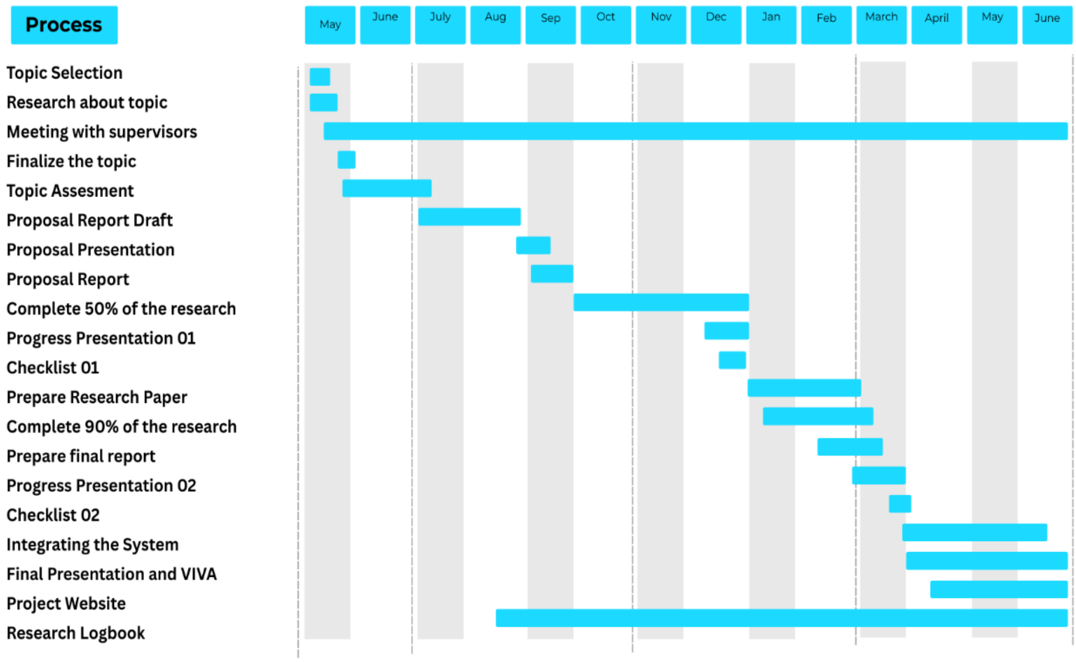
3.2 Component Overview Diagram

3.4 Work Breakdown Structure



3.3Work Breakdown Structure

4. GANTT CHART



5. PROJECT REQUIREMENTS

5.1 Functional Requirements

Functional requirements describe what the system should do. They define the core features and services needed to achieve the project objectives. For this project, the functional requirements are:

- **Disengagement Detection**-The system shall continuously monitor student activity data (including logins, session duration, task completion, and interaction responses) and identify students showing early signs of disengagement or dropout risk.
- **Adaptive Interventions**-The system shall deliver adaptive interventions to at-risk students by selecting the most suitable timing, communication channel, and message tone based on each student's prior responses and behavior trends.
- **Survey and Sentiment Capture**-The system shall present short in-app surveys to flagged students to capture their personal blockers (such as time constraints, motivation issues, content difficulty, technical problems) and self-reported mood levels and shall apply sentiment analysis on short free-text replies to detect emotional tone.
- **Guidance Delivery**-The system shall provide pre-set supportive guidance templates based on survey and sentiment results, such as motivational prompts, micro-planning nudges, stress-reduction reminders, or helpdesk contact messages.
- **Social Engagement Layer**-If students continue ignoring system interventions, the system shall activate a peer support mechanism where selected peers can send supportive "peer cheers" as friendly messages to help rebuild motivation through positive social presence.
- **Escalation Mechanism**-The system shall escalate severe or persistent disengagement cases to academic staff through a dedicated dashboard that includes recent activity data, sentiment trends, survey responses, and suggested outreach scripts for personal follow-up.

- **Sustained Engagement Tracking**-The system shall track returning students over time and mark them as fully re-engaged only when they maintain consistent activity levels for a defined period, rather than showing temporary spikes.
- **Notifications**-The system shall deliver real-time alerts, guidance, and updates to students through in-app notifications, email, or SMS, based on their communication preferences.
- **Dashboard Interface**-The system shall provide dashboards for students, peers, and academic staff, presenting engagement insights, alerts, supportive messages, sentiment trends, and follow-up tools in an accessible and user-friendly format.

5.2 Non-Functional Requirements

Non-functional requirements describe how the system should perform. They focus on quality attributes rather than specific features. For this project, the non-functional requirements include:

- **Scalability** - The system should support a large number of students, peers, and staff users simultaneously without performance degradation, utilizing cloud-based infrastructure and auto-scaling mechanisms.
- **Reliability** - The system should provide consistent and accurate disengagement detection and intervention services with minimal downtime and robust error handling.
- **Performance** - The system should process student activity data and deliver notifications in real time, ensuring timely interventions without noticeable delays.
- **Security** - All sensitive student data, including engagement logs, sentiment outputs, and survey responses, must be securely stored and transmitted using encryption, access control, and secure authentication methods.

- **Usability**- The dashboards, surveys, and messaging interfaces should be simple, intuitive, and accessible to ensure ease of use for students, peers, and academic staff.
- **Maintainability** - The system should be designed in a modular and well-documented manner to allow easy updates, extensions, and integration with future academic technologies.
- **Privacy** - Student responses, mood information, and personal engagement data should be handled ethically and confidentially, in compliance with institutional data protection and privacy policies.

5.3 User Requirements

User requirements describe what users expect from the system to support their roles effectively. They outline the essential capabilities needed to ensure a smooth and supportive user experience.

- Users should be able to view a personalized dashboard showing their recent engagement activity and status.
- Users should be able to receive system alerts, guidance messages, and notifications through their preferred channels (in-app, email, or SMS).
- Users should be able to complete short in-app surveys to report personal blockers and current mood levels.
- Users should be able to receive supportive guidance messages, including motivational prompts, planning tips, stress-reduction reminders, and helpdesk contacts.
- Users should be able to send and receive supportive peer messages when the social engagement layer is activated.
- Users should be able to view alerts, engagement insights, survey results, and guidance history on their dashboard.
- Users should be able to access real-time updates and messages without needing to refresh or reload the system.

- Users should be able to receive timely support from academic staff if they are flagged as high-risk or severely disengaged.
- Users should be able to interact with a simple, intuitive, and accessible interface with clear navigation and feedback.

5.4 Expected Test Cases

The following test cases are expected to validate the functionality and reliability of the proposed system:

1. **Login Frequency Detection**

   Input: Student logs in irregularly (e.g., less than two times per week)

   Expected Output: System flags the student as "Low Engagement" and stores the updated risk level in the database.

2. **Alert Interaction Response**

   Input: System sends adaptive reminders, and the student ignores multiple consecutive alerts

   Expected Output: Disengagement model raises the risk level; RL model shifts strategy by changing the communication channel or timing for future alerts.

3. **Re-Engagement through RL**

   Input: Student previously ignored in-app alerts, and the system resends using SMS

   Expected Output: Student re-engages (login within 24 hours); RL model records a positive reward for the chosen action.

4. **Survey and Sentiment-Based Escalation**

Input: Student completes a survey indicating time pressure and writes a stressed comment detected as negative sentiment

Expected Output: System categorizes mood as "Very Low" and generates an escalation flag on the staff dashboard.

5. **Continuous Active Engagement**

   Input: Student logs in regularly, completes tasks, and responds to alerts

   Expected Output: System classifies the student as "Normal Engagement" and stops sending further alerts.

6. **Disengagement Detection Edge Case**

   Input: Student logs in frequently but ignores all alerts

   Expected Output: Disengagement model identifies a hidden disengagement pattern based on interaction drop and updates classification.

7. **Peer Cheer Activation**

   Input: Student repeatedly ignores system interventions despite escalating alerts

   Expected Output: System activates the peer engagement layer and notifies selected peers to send supportive messages.

8. **Adaptive Policy Improvement**

   Input: Multiple students show better responses to evening reminders than morning ones

   Expected Output**:** RL model updates its policy to prioritize evening scheduling for similar student profiles.

6. DESCRIPTION OF PERSONAL AND FACILITIES

Registration No	Name	Task Description
IT22902702	Perera I.A.T.D	• The project is carried out by a dedicated student research team, guided and supervised by academic staff for technical and methodological support. • Work is conducted using personal laptops and university lab computers equipped with the necessary specifications for coding, data analysis, and testing. • Common software tools such as Python, Java, React, TensorFlow, PyTorch, and Firebase are used throughout development. • Reliable internet access at both home and university ensures smooth collaboration, cloud access, and literature review.

Table 6.1.Description of personal and facilities

7. BUDGET AND BUDGET JUSTIFICATION

Description	**Total Amount (Rs.)**
Email & SMS Gateway Service (6 months)	10,000
Firebase (paid tier for alerts & notifications)	10,000
Cloud Deployment (AWS/GCP/Azure – compute & storage)	25,000
Total Budget	45,000

Table 7.1.Estimated budget table

8.ABILITY OF COMMERCIALIZATION

The proposed system demonstrates strong potential for commercialization and entrepreneurship due to its clear market demand, scalable architecture, and measurable impact on student success. Educational institutions face growing pressure to reduce dropout rates and improve student retention, yet most existing platforms stop at predictive alerts without providing active re-engagement pathways. This system closes that gap by combining predictive analytics, adaptive reinforcement learning interventions, emotion-aware feedback, social peer support, and structured staff escalation, making it uniquely positioned as a complete engagement recovery solution.

The platform can be offered to universities, private higher education institutes, and large online learning providers as a subscription-based Software-as-a-Service (SaaS) model. Institutions can integrate it with their existing LMS platforms to automatically detect disengaged students, deliver supportive guidance, and route serious cases to staff for timely follow-up. This reduces manual workload on academic advisors and directly improves student retention rates, which has a significant financial benefit for institutions.

Beyond higher education, the system can be extended to corporate e-learning, professional certification programs, and MOOC platforms, where disengagement is also a critical issue. Its modular design, real-time notification system, and scalable cloud infrastructure make it technically and commercially viable to deploy across multiple sectors.

In summary, this solution offers clear user benefits (personalized support, improved engagement, reduced dropout), operational benefits (automated intervention and monitoring), and strong business potential (institutional licensing, SaaS delivery, and cross-sector applicability), demonstrating its suitability for entrepreneurial commercialization.

References

[1] K. E. Arnold and M. D. Pistilli, "Course Signals at Purdue: Using Learning Analytics to Increase Student Success," *Proc. 2nd Int. Conf. Learning Analytics and Knowledge*, pp. 267–270, 2012.

[2] S. M. Jayaprakash, E. W. Moody, E. J. M. Lauría, J. R. Regan, and J. D. Baron, "Early Alert of Academically At-Risk Students: An Open-Source Analytics Initiative," *Journal of Learning Analytics*, vol. 1, no. 1, pp. 6–47, 2014.

[3] R. F. Kizilcec, C. Piech, and E. Schneider, "Deconstructing Disengagement: Analyzing Learner Subpopulations in MOOCs," *Proc. 3rd Int. Conf. Learning Analytics and Knowledge*, pp. 170–179, 2013.

[4] M. Wen, D. Yang, and C. P. Rosé, "Sentiment Analysis in MOOC Discussion Forums: What Does it Tell Us?," *Proc. 7th Int. Conf. Educational Data Mining*, pp. 130–137, 2014.

[5] C. Taylor, K. Veeramachaneni, and U.-M. O'Reilly, "Likely to Stop? Predicting Stopout in MOOCs," *MIT Office of Digital Learning Research Report*, 2014.

[6] J. Whitehill, J. J. Williams, G. Lopez, C. Coleman, and J. Reich, "Beyond Prediction: First Steps Toward Automatic Intervention in MOOC Student Stopout," *Proc. Educational Data Mining*, pp. 171–178, 2015.

[7] D. Bañeres, M. E. Rodríguez, and A. E. Guerrero-Roldán, "An Early Warning System to Detect At-Risk Students in Online Higher Education," *Applied Sciences*, vol. 10, no. 13, p. 4427, 2020.

[9] A. L. Brooks, M. Carroll, and C. Giles, "Social Belonging Interventions Improve Student Retention in Online Learning," *Computers & Education*, vol. 193, p. 104654, 2023.

[10] Y. Liu, L. Chen, and Z. Wang, "Reinforcement Learning for Personalized Education: A Survey," *IEEE Transactions on Learning Technologies*, vol. 16, no. 2, pp. 228–243, 2023.

APPENDIX

IT22902702.pdf

ORIGINALITY REPORT

8%	7%	1%	7%
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	1%
3	Submitted to Arab Open University Student Paper	1%
4	Submitted to College of Engineering, Pune Student Paper	<1%
5	cimmar.unizd.hr Internet Source	<1%
6	cirworld.org Internet Source	<1%
7	slashdot.org Internet Source	<1%
8	Submitted to BBPlugin Student Paper	<1%
9	Submitted to Southern New Hampshire University - Continuing Education Student Paper	<1%
10	www.qservicesit.com Internet Source	<1%
11	sairamce.edu.in Internet Source	<1%
12	www3.nd.edu Internet Source	<1%