

**ADAPTIVE AND EXPLAINABLE AI FOR STUDENT
RISK PREDICTION AND PERSONALIZED ACADEMIC
INTERVENTIONS: A CONTINUOUS LEARNING
ANALYTICS FRAMEWORK**

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**STUDENT DISENGAGEMENT DETECTION AND
PERSONALIZED SUPPORT SYSTEM FOR
RE ENGAGEMENT**

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Dissertation submitted in partial fulfilment of the requirements for the Bachelor of
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DECLARATION

I declare that this is my own work and this dissertation 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 my 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.

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ABSTRACT

In recent years, student disengagement has emerged as a major problem in online and digital learning environments, where students tend to decrease their engagement levels without early detection. This impacts student learning outcomes, raises the risk of dropout and reduces the impact of early academic intervention. The current systems primarily focus on final grades or basic user activity, making them reactive and incapable of detecting early signs. This creates a significant need for a system capable of proactively monitoring and supporting students with timely and personalized interventions.

In this study, we propose AcademiGuard, an AI-based full-stack student monitoring and intervention model to detect early disengagement and help re-engage. AcademiGuard is developed with a React-based frontend for interactive dashboards, Firebase Cloud Functions to provide the API server, Firestore to store and update student data in real-time and FastAPI for the machine learning microservice. The system in its entirety tracks student behaviour patterns, including logins, time spent and engagement, to detect unusual learning patterns.

The key component of this research is the Student Disengagement Detection and Personalized Support System, which integrates a GRU Autoencoder and a Reinforcement Learning (RL) decision model. The GRU Autoencoder model helps to analyse sequential behavioural data and identify anomalies using reconstruction error, enabling the platform to categorize students into various risk levels. The RL model then determines the optimal intervention strategy (such as gentle reminders, peer encouragement or human intervention) based on risk levels and behavioural patterns. This helps to provide appropriate support to students while avoiding alert fatigue.

To enhance the model's trustworthiness and user-friendliness, we also provide explainable insights and dashboards to lecturers and students, explaining how risk levels are calculated and interventions deployed. The system will be designed to simulate a real-world academic environment, with the weekly student data processed, analysed and updated to show a full end-to-end process.

The results of this project are expected to lead to better early detection of risk patterns, effective and dynamic intervention strategies and better student re-engagement. Through this journey from a reactive to a proactive and smart intervention, this project seeks to mitigate the risk of student drop out and improve learning outcomes and success rates in higher education settings.

Keywords – Student Disengagement, Early Detection, GRU Autoencoder, Reinforcement Learning, Personalized Interventions, Learning Analytics, Predictive Modeling, Educational Data Mining, Academic Risk Prediction, Explainable AI, Smart Learning Systems

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LIST OF ABBREVIATION

Abbreviation	Description
AI	Artificial Intelligence
ML	Machine Learning
GRU	Long Short-Term Memory
RL	Reinforcement Learning
LMS	Learning Management System
API	Application Programming Interface
NLP	Natural Language Processing
LA	Learning Analytics

1. INTRODUCTION

With the increasing use of online learning, student engagement is a critical issue in higher education today. Institutions are now adopting Learning Management Systems (LMS), online learning resources and independent study, which offer convenience but also decrease supervision. This has made it harder for lecturers to spot the early signs of disengagement. Students can often lower their engagement by not interacting with activities or logging in less often, but this can go unnoticed until the decline is more acute. Such "invisible" disengagement can impact on academic achievement, contribute to drop-out and ultimately affect the student experience.

Students today also face multiple pressures at the same time, including academic workload, tight deadlines, personal responsibilities, and adapting to independent learning. These factors can cause low motivation and erratic study habits. Sometimes disengagement occurs in a progressive manner. Research indicates that many university students face multiple academic and psychological challenges in this transition phase, which also leads to disengagement [1]. But the majority of current academic monitoring systems are primarily concerned with final grades, attendance or activity logs. These solutions are more reactive than proactive and only detect issues after academic performance has declined. This is why it is important to develop a more proactive system that can monitor students on a continuous basis and identify early signs of trouble.

In this research, we propose AcademiGuard, an AI-based real-time student engagement monitoring system that delivers timely feedback to students. This system is developed with a modern architecture that includes a React-based front-end for interactive dashboards, Firebase Cloud Functions as the back-end API, Firestore for real-time data storage and a FastAPI-based machine learning microservice. This architecture enables the system to process student behaviour data in real time, and to provide timely insights to students and lecturers.

This individual project focuses on the Student Disengagement Detection and Personalized Support System, which seeks to detect early signs of disengagement and suggest interventions. This is done through a GRU Autoencoder model that processes time-series behavioural data, such as the number of logins, length of sessions and patterns of activity. The GRU Autoencoder learns to replicate normal student behaviour and identifies outliers by measuring reconstruction loss. If a student's behaviour is significantly different from the normal behaviour, it is flagged as being at risk of disengagement. This method is very effective as it can model temporal information and small behavioural changes often overlooked by rule-based or static models. Prior studies have demonstrated that deep learning models like GRU and LSTM are very effective in modelling sequence-based behaviour in education [2].

Once the student has been identified as being disengaged, the system uses a Reinforcement Learning (RL) model to decide on an intervention strategy. The RL

model is used to determine the best possible action, which can vary for different students, depending on the disengagement risk, trend, and previous student response. These interventions include gentle reminders, peer messaging, or interventions by academic staff if required. The model aims to maximise student engagement over time while minimising the number of notifications, which can cause fatigue. Reinforcement learning has been extensively applied in adaptive systems to enhance user experience and achieve long-term goals [3].

Another key feature of the system is its ability to simulate a real-world academic workflow. The system continually gathers student data, which is analysed weekly, enabling it to monitor student engagement patterns. This information is then presented in dashboards, aiding lecturers in interpreting student engagement and making decisions. This closed-loop process illustrates how machine learning models can be applied to educational systems to generate valuable insights.

In conclusion, this work aims to move from traditional reactive to proactive by providing an intelligent system for monitoring student engagement. The integration of deep learning for analysing student behaviour and reinforcement learning for adaptive interventions ensures early intervention, personalisation and continuous optimisation of student engagement. This helps to prevent student drop-out, boost academic achievement and increase the learning experience in the digital age.

1.1 Background and Literature Survey

Background

In recent years, the move towards online and hybrid learning in higher education has made tracking student engagement more complex. Digital learning environments like Learning Management Systems (LMS) and other online platforms offer flexibility and convenience, but also limit student-lecturer interaction. This makes it challenging to detect disengagement early, particularly when students start to withdraw slowly without obvious symptoms. This problem has gained more urgency in recent years as research suggests many university students have difficulties sustaining engagement in online and blended learning [1]. Disengagement is not an overnight phenomenon but a progressive process, affected by various factors including stress, motivation, time management, and social interaction with other students and lecturers. This can ultimately result in poor student performance and even drop-out, if not identified early. This behaviour monitoring has been done traditionally through grade evaluation and attendance monitoring, which is not fine-grained enough to understand trends. These are largely reactive, and only detect problems once they have developed. As a result, there is a clear need for new methods that can proactively track student behaviour and identify potential issues early on. Meanwhile, the importance of data-driven technologies for education, referred to as learning analytics, has become more and more prominent. This can be achieved by examining interaction data, including the number of logins, time spent on learning resources and engagement in activities. But many of the current analytics solutions use basic statistical approaches or rule-based systems, which do not account for complex temporal patterns in student engagement. The latest developments in machine learning, such as deep learning techniques, have demonstrated encouraging progress in this area [2].

Literature Survey

Research on student engagement and predictive analytics highlights several important developments that directly relate to this study.

A key focus is on the use of deep learning models that know how to deal with sequences for student behaviour analysis. Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) models are commonly used in time series analysis. Recently, GRU models have been used for capturing temporal dynamics with reduced complexity compared to LSTM. Recent research has shown that GRU models can be used to identify anomalies and predict trends in educational data [2]. Specifically, autoencoder models enable the system to learn the natural behaviour and detect anomalies based on the reconstruction error, which can be used for unsupervised disengagement detection.

Another key area of research is anomaly detection in education data mining. Anomaly detection differs from classification approaches in that it aims to identify anomalies without the need for labelled data. This is particularly valuable in practical educational settings where the availability of disengagement labels is not guaranteed. Chandola et

al. [3] point out that anomaly detection techniques are well suited to detect unusual patterns in sequence data, in line with the aim of identifying early disengagement indicators.

Besides detection, timely intervention is crucial. Recent research highlights the role of adaptive and personalised interventions to enhance student learning. Reinforcement Learning (RL) is a promising framework for decision-making. RL models adapt to the environment and learn optimal policies, rather than relying on pre-defined rules, which makes them an attractive option for intervention selection based on student performance. Sutton and Barto [4] provide a basis for RL as a foundation for adaptive systems, and recent work demonstrates its success in educational recommendation systems and personalised learning systems.

Moreover, the idea of adaptive intervention strategies has been applied in other areas, where systems dynamically adapt interventions based on user behaviour. In education, this includes actions such as reminders, motivational prompts and teacher intervention. Research shows that timely and targeted interventions are effective in increasing user engagement compared to standard notifications [5]. But many current systems still use hard-coded rules or simple heuristics to decide what action to take, reducing their effectiveness in responding to individual needs.

Another important problem described in the literature is user disengagement from the support system due to alert fatigue. Students can easily become overwhelmed by irrelevant or repeating messages, and stop engaging with the system. As a result, the current focus is on providing smart decision-making strategies that strike a balance between intervention and efficacy [5].

Based on these findings, it is clear that an effective student engagement system must combine accurate behavioural analysis with adaptive intervention strategies. Some studies have examined these aspects separately, but there is a lack of research that combines anomaly-based disengagement detection with reinforcement learning-based intervention.

This study aims to fill this gap by integrating a GRU Autoencoder-based model for disengagement detection and a Reinforcement Learning-based model for intervention strategies. The integration of these methods into a real-time, full-stack system allows the proposed system to go beyond reactive approaches and offers an advanced, data-driven approach to enhancing student engagement and preventing drop-out.

1.2 Research Gap

While numerous research and systems have focused on monitoring student engagement and providing online support, there are still key gaps in current methods. The majority of existing studies are either centred on prediction or intervention, but few systems integrate these approaches in real time. From reviewing the major existing solutions such as learning analytics (LA) systems, deep learning prediction models and adaptive intervention systems, we can see that there are still the following research gaps.

Table 1 Comparison of the existing research methods and proposed method

Feature	[2]	[3]	[4]	[5]	Our Solution
Sequential Behaviour Analysis (Time-Series)	✓	×	×	×	✓
Anomaly-based Disengagement Detection	✓	✓	×	×	✓
Real-time Risk Identification	×	×	✓	×	✓
Adaptive Personalized Interventions	×	×	✓	✓	✓
Reinforcement Learning-based Decision Making	×	×	×	✓	✓
Peer-based Support (Peer Cheer)	×	×	×	×	✓
Human-in-the-loop Escalation (Instructor Support)	×	×	×	×	✓
End-to-End Integrated System (Detection + Action)	×	×	×	×	✓

Existing research using deep learning models such as GRU and RNN has shown strong capability in analysing sequential behavioural data and identifying patterns over time [2]. These models are good at identifying trends but are primarily used for prediction and do not provide tools for intervention. Likewise, anomaly detection methods are effective in detecting abnormal student behaviour without the need for labels [3]. But these approaches generally do not provide interventions.

On the other hand, learning analytics systems provide dashboards and engagement metrics to support decision-making [5]. They can offer some insights, but usually rely on fixed rules or thresholds, and are not adaptive or personalized.

The topic of adaptive decision-making and personalisation has also been extensively researched using reinforcement learning [4]. But most of these approaches do not combine RL with real-time behavioural assessment and they do not provide multi-level intervention strategies, such as peer cheer and human escalation.

A significant research gap is the lack of social and human-based interventions in automation. Current approaches only use notifications or recommendations, without incorporating social engagement (peer cheer) or escalation to lecturers on critical risk.

Therefore, the key research gap is the lack of a fully integrated, proactive system that combines anomaly-based disengagement detection with adaptive, multi-level intervention strategies, including automated notifications, peer-based encouragement, and human support mechanisms.

This research addresses that gap by designing a system that not only detects disengagement using a GRU Autoencoder but also responds intelligently using a Reinforcement Learning model, incorporating soft nudges, reminders, peer cheer, and human escalation within a unified framework.

1.3 Research Problem

Student disengagement has become a critical issue in modern higher education, particularly in digital and blended learning environments. Many students experience academic and psychological issues affecting their engagement and learning [1]. However, identifying disengagement at an early stage remains difficult due to the gradual and hidden nature of behavioural changes.

Current systems have several shortcomings. First, most existing academic monitoring systems are passive, and based only on final exam scores or attendance records, which indicate issues after they have arisen. Second, although machine learning approaches like GRU and anomaly detection methods can detect changes in behaviour, they usually focus only on prediction [2], [3]. Third, intervention systems typically use static or non-personalised notifications, which do not account for individual needs and can decrease effectiveness [5].

Fourth, existing systems don't appropriately consider multi-level interventions. For instance, students at low risk may only need reminders, whereas students at high risk may need support from peers or the lecturer. But current approaches do not allow escalation of support according to risk and response.

A further problem is the lack of a connection between detection and escalation. While reinforcement learning offers a strong framework for decision-making, it is not often linked with the real-time on-task detection models [4]. What's missing is also peer-based engagement (peer cheer) and human-in-the-loop support (lecturer escalation), which also contributes to the effectiveness of intervention decisions.

There's also the problem of notification fatigue, where students can overlook irrelevant or redundant notifications. This suggests the need for a system that can not only choose the appropriate intervention but also the timing and intensity.

Given these challenges, the research question is:

How can a proactive, AI-driven system be developed to accurately detect student disengagement using behavioural data and provide personalized, adaptive, and multi-level interventions, including automated alerts, peer support, and human escalation. in real time, while minimizing alert fatigue and improving long-term student engagement?

This research aims to solve this problem by developing a unified system that integrates a GRU Autoencoder-based anomaly detection system with a Reinforcement Learning-based intervention decision-making system. The system adopts a multi-level intervention approach, including gentle nudges, reminders, peer encouragement and human intervention, to ensure students get the right level of support based on their engagement status. Through this integration of prediction and intervention, the system will offer a more efficient and effective way of managing student engagement.

1.4 Research Objectives

1.4.1 Main Objective

The main goal of this research is to design and develop an AI-powered system to detect student disengagement early and provide personalized, adaptive support in a proactive manner. Instead of waiting until academic performance drops, this system focuses on identifying behavioral changes in advance and responding with the most suitable intervention.

The core idea is to build an intelligent solution that continuously monitors student activity patterns and transforms them into meaningful insights. By analyzing sequential behavioral data such as login frequency, session duration, and engagement trends, the system aims to recognize hidden patterns that indicate disengagement.

Based on this analysis, the system will automatically select and deliver appropriate interventions using an adaptive decision-making approach. These interventions are designed to support students at different levels, starting from simple reminders and gradually moving towards peer encouragement and human support when necessary.

Overall, the objective is to create a complete and continuous workflow that connects data collection, behavioral analysis, and intervention delivery. This will help improve student engagement, reduce dropout risk, and support better academic outcomes through timely and personalized actions.

1.4.2 Specific Objectives

1. To develop a behavioral data analysis model for detecting student disengagement

This objective focuses on building the core detection mechanism of the system. It involves analyzing student behavioral data collected over time, such as login activity, session duration, and learning interactions. Since this data is sequential in nature, a GRU Autoencoder model will be used to learn normal behavior patterns and identify anomalies through reconstruction error. The model will classify students into different risk levels based on their engagement behavior, enabling early detection of disengagement before academic performance is affected.

2. To design and implement a reinforcement learning-based intervention engine

The aim is to build a dynamic decision-making engine that will decide on the best intervention for each student. The reinforcement learning algorithm will take into account the degree of risk, the trend of behaviour, past actions and past responses of

the student. Using this data, the system will select actions like gentle nudges, reminders, peer encouragement or human escalation. The aim is to ensure the intervention is effective without bombarding the students with excessive or redundant notifications.

3. To develop a multi-level intervention strategy for personalized student support

This goal is to establish and execute a layered intervention strategy based on engagement. Students at low risk will be provided with light touch interventions (such as nudge reminders) and those at higher risk will be supported through more intensive interventions (such as peer or lecturer support). This layered strategy ensures that support is both personalized and context-aware, improving student responsiveness and engagement over time.

4. To design and implement a real-time data processing and integration workflow

This goal deals with the system integration of data collection, machine learning, and data storage. The system will collect student data every week, feed it into the machine learning service for predictions, and store the predictions in a database. This ongoing process allows the monitoring of engagement over a period of time, and makes the detection and intervention processes real-time and scalable.

5. To evaluate the effectiveness of the proposed system in improving student engagement

This goal is to evaluate the effectiveness of the system in practice. The evaluation will consider factors such as accuracy of disengagement detection, relevance of selected interventions, and overall improvement in student engagement. We will use user feedback, logs and patterns to determine the effectiveness of the system in decreasing disengagement and promoting re-engagement.

2. METHODOLOGY

2.1 Methodology

The approach of this research is a scalable, layered system design that divides the user interface from the machine learning system. This enables a responsive user interface while allowing machine learning processing to focus on data analysis and decision making.

The system operates as a continuous feedback loop. The system analyses data on student behaviours to identify disengagement patterns, and based on this analysis, recommends interventions. These are returned to the user or other stakeholders, and the process continues in an iterative manner.

2.1.1 System Architecture and Technologies

The overall system architecture consists of three main components: frontend, backend, and machine learning microservices.

- **Frontend (User Interface):**

The frontend of the system is developed using React, providing an interactive dashboard for both students and lecturers. It allows users to view engagement levels, track historical data, and receive system-generated interventions. The interface is designed to be simple and user-friendly, ensuring easy navigation and minimal cognitive load. Communication between the frontend and backend is handled through REST APIs.

- **Backend and Database:**

Firebase Cloud Functions are used for implementing the backend as the API layer for request processing and system coordination. The system uses Firebase Firestore as the primary database to store student information, weekly behavior logs, disengagement risk status and intervention logs. Firebase Authentication is used for secure authentication. This approach guarantees scalability, real-time data and data efficiency.

- **Machine Learning Services:**

The system's intelligence is realized as a FastAPI Python microservice. It's responsible for detecting disengagement and making intervention decisions. Machine learning models are trained using packages like TensorFlow and Scikit-learn. The microservice-based design enables independent execution of the models and allows for easy replacement or scaling.

2.1.2 Data Flow and Process

The system follows a structured data flow that connects user data, machine learning models, and intervention delivery:

- **Data Collection:**

Weekly data regarding the number of logins, time spent, active time and patterns of interaction is gathered from students and stored in Firestore.

- **Backend Processing:**

Once data is ready, Firebase Cloud Functions pull the appropriate data for analysis. The most recent 10 weeks of behavioral data are chosen to create a sequence of data for the machine learning model.

- **AI Analysis:**

- **Disengagement Detection Model (GRU Autoencoder):**

The student behavior data is given to the GRU Autoencoder. It is trained to capture the behavior patterns of students and reconstruct data. The reconstruction error (difference between the original data and the reconstructed data) is computed. Greater error suggests abnormal behavior, and thus a higher risk of disengagement. The system categorizes the students according to the threshold-defined risk level (e.g., low, normal, or high).

- **Adaptive Intervention Model (Reinforcement Learning):**

Once the risk level is identified, the system passes the result to the reinforcement learning model. This model considers multiple factors including current risk level, behavioral trend, previous actions, and response history. Based on this state, the model selects the most appropriate intervention. The available actions include soft nudges, reminders, peer cheer, and human escalation. The goal is to choose the most effective action while minimizing unnecessary notifications.

- **Data Storage and Feedback Loop:**

The prediction outcomes and interventions are recorded in Firestore. This information is used to monitor student learning and update system state variables for future predictions.

- **User Interaction:**

The selected interventions are delivered to students or lecturers through the frontend dashboard or notification system. This completes the feedback loop, where system outputs influence future user behavior and data.

2.1.3 Application of Knowledge Domains

- **Machine Learning:**

Used for analyzing student behavioral data, detecting disengagement patterns, and making adaptive intervention decisions.

- **Deep Learning:**

The GRU Autoencoder model is used for sequential pattern analysis and anomaly detection in time-series data.

- **Reinforcement Learning:**

Applied for selecting optimal intervention strategies based on student behavior and system feedback.

- **Cloud Computing:**

Firebase provides a scalable backend environment for real-time data processing, storage, and authentication.

- **Web Technologies:**

React is used to build interactive dashboards and ensure a responsive user experience.

2.1.4 Expected Outcomes

- Accurate detection of student disengagement using behavioral data patterns and reconstruction error analysis.

- Effective selection of personalized interventions using reinforcement learning, improving student responsiveness and engagement.

- Implementation of a multi-level support system including soft nudges, reminders, peer cheer, and human support.

- A fully integrated system that connects data collection, prediction, and intervention in a continuous workflow.

- Improved student engagement and reduced dropout risk through proactive and adaptive support mechanisms.

2.1.5 System Architecture

System Overview

The system begins with the user interacting through the web-based interface, where student behavioral data such as login activity, session duration, and engagement metrics are either collected automatically or uploaded as weekly records. These inputs are sent through REST API endpoints to the backend system and processed in the data preparation stage before being stored in the Firestore database.

The prepared data is then analyzed through two main intelligent components: the disengagement detection model and the adaptive intervention engine. The GRU Autoencoder model processes sequential behavioral data to identify patterns and calculate reconstruction error, which is used to determine the student's disengagement risk level. This allows the system to detect early signs of reduced engagement based on behavioral changes over time.

Once the risk level is identified, the data is passed to the reinforcement learning-based decision engine. This component evaluates the current state of the student, including risk level, engagement trend, previous interventions, and response history. Based on this analysis, the system selects the most appropriate intervention strategy from a set of actions such as soft nudges, reminders, peer cheer, or human support escalation.

The results of both models are stored in the database and used to maintain a continuous history of student engagement and system decisions. This historical data supports future predictions and helps improve the accuracy of intervention selection.

Finally, the system delivers outputs back to the user through the interface. These outputs include disengagement risk levels, personalized intervention actions, and visual representations of engagement trends. Notifications and alerts are also generated to ensure timely support. This creates a complete feedback loop where user data is continuously analyzed and used to provide proactive and adaptive support, improving overall student engagement and academic outcomes.

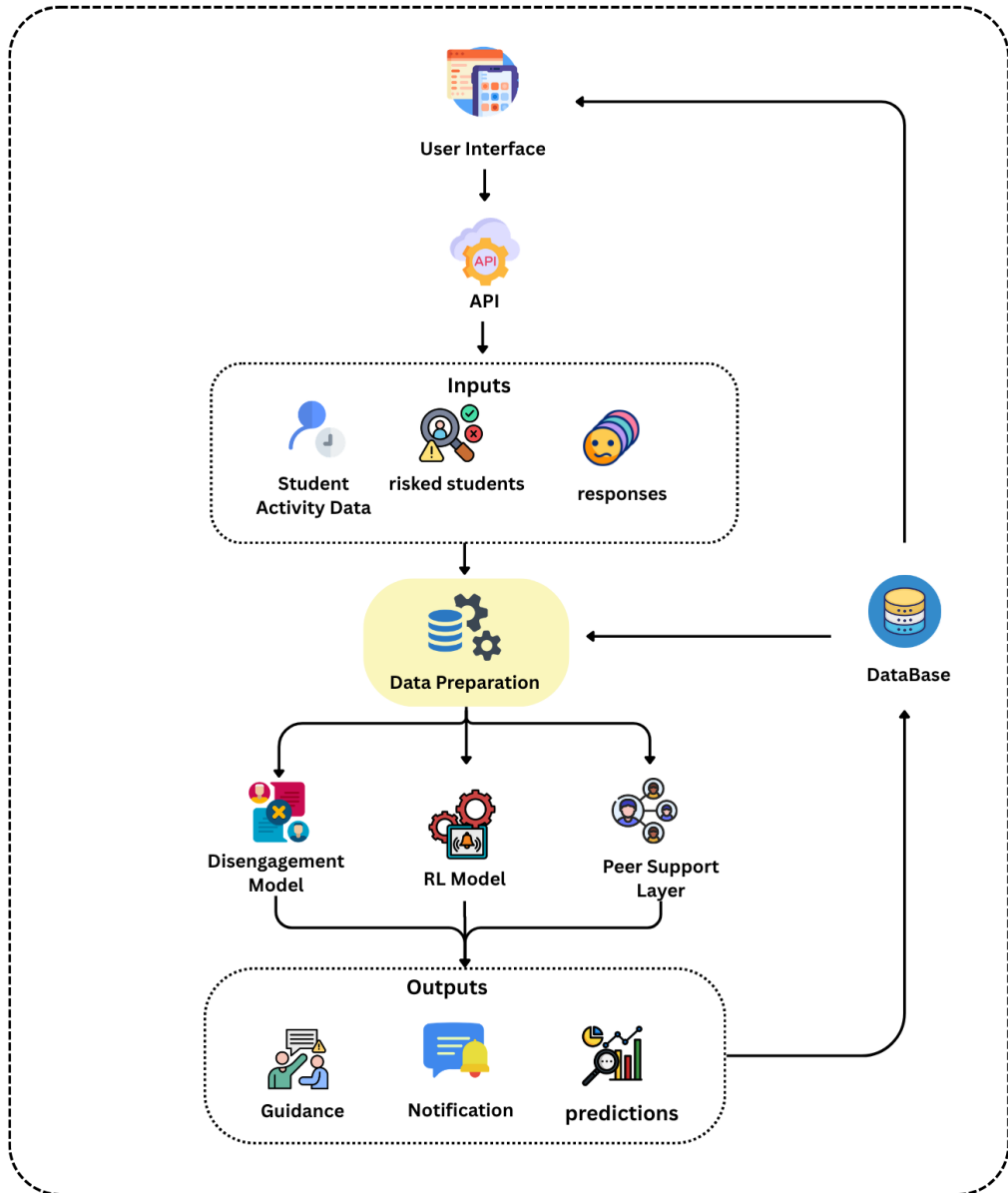


Figure 1 System Architecture

2.2 Project Requirements

2.2.1 Functional Requirements

- The system shall collect and store student behavioural data such as login activity, session duration, and engagement metrics.
- The system shall process sequential behavioural data (last 10 weeks) for each student.
- The system must analyse student behaviour using a GRU Autoencoder to detect disengagement patterns.
- The system shall classify students into different risk levels (e.g., low, normal, high) based on reconstruction error.
- The system must determine the most appropriate intervention using a reinforcement learning model.
- The system shall support multiple intervention actions, including soft nudges, reminders, peer cheer, and human support escalation.
- The system shall store prediction results and intervention history for each student.
- The system shall display student engagement levels and trends through a dashboard interface.
- The system shall generate notifications and alerts based on detected risk levels.
- The system shall allow lecturers or administrators to monitor student engagement and take necessary actions.

2.2.2 Non-Functional Requirements

- Performance: The system must process behavioural data and generate predictions within a short time to enable near real-time decision-making.
- Usability: The user interface must be simple, clear, and easy to use for both students and lecturers.
- Scalability: The backend system must handle increasing numbers of students and large volumes of behavioural data efficiently.

- **Reliability:** The system must ensure consistent performance and accurate prediction results across multiple runs.
- **Security:** All student data must be securely stored and protected using proper authentication and access control mechanisms.
- **Maintainability:** The system should be designed in a modular way, allowing easy updates to machine learning models and system components.

2.2.3 User Requirements

- The system should help students stay engaged in their studies by identifying disengagement early.
- The system should automatically analyse student behaviour without requiring manual input.
- The system should provide appropriate support based on each student's engagement level.
- The system should deliver personalized interventions such as reminders, peer encouragement, or lecturer support when needed.
- The system should allow lecturers to easily monitor student engagement and identify at-risk students.
- The system should provide clear insights and visualizations to help users understand engagement trends.

2.3 Commercialization Strategies

2.3.1 Commercialization and Revenue Opportunities

The main goal of commercialization is to develop a sustainable and scalable model that allows the system to be widely used by educational institutions while ensuring long-term maintenance and improvement. The proposed strategies focus on delivering value through proactive engagement monitoring and adaptive intervention capabilities.

1. Freemium Model:

The free version of the system will provide basic engagement monitoring features for students and lecturers. This includes tracking student behavioral data, displaying basic engagement levels, and providing simple notifications such as reminders. It will allow users to understand general engagement trends but with limited access to advanced analytics and intervention features.

2. Premium Model:

The premium version will unlock the full capabilities of the system, including advanced disengagement detection using the GRU Autoencoder model and adaptive intervention selection using reinforcement learning. Users will receive personalized interventions such as soft nudges, reminders, peer cheer, and human support escalation. In addition, the premium version will include detailed dashboards, engagement trend analysis, and historical insights. This model provides significant added value compared to traditional monitoring systems by offering proactive and intelligent support.

3. Institutional Partnerships:

Educational institutions can adopt the system through a licensing model. Universities or schools will pay an annual subscription fee based on the number of students. In return, all students and lecturers will gain access to the full system features. This approach benefits institutions by improving student engagement, reducing dropout rates, and enhancing academic performance. It also supports data-driven decision-making for academic staff and administrators.

2.3.2 User Opportunities Compared to Traditional Counselling

1. Continuous Monitoring:

Unlike traditional methods that rely on attendance or final grades, this system continuously tracks student behavior over time. This allows early identification of disengagement before academic performance is affected.

2. Proactive Support:

The system provides interventions before problems become critical. Instead of reacting after poor results, students receive timely support such as reminders, peer encouragement, or lecturer involvement based on their engagement level.

3. Personalized Interventions:

Using reinforcement learning, the system selects the most suitable intervention for each student. This ensures that support is relevant and effective, rather than using the same approach for all users.

4. Multi-Level Support System:

The platform provides different levels of support, including automated alerts, peer cheer, and human escalation. This creates a more complete support system compared to traditional approaches that depend only on lecturers or counsellors.

5. Data-Driven Insights:

Students and lecturers can view engagement trends and behavioral patterns through dashboards. This helps users understand learning habits and take corrective actions early.

6. Scalability and Accessibility:

The system can support a large number of students through a cloud-based architecture, making it suitable for institutions of different sizes. It is accessible through a web interface, allowing users to interact with the system anytime and from any location.

2.4 Test Cases

Table 2 Test Case1 Disengagement Detection using GRU Model

Test Case ID	TC-01	
Test Scenario	Disengagement Detection using GRU Model	
Preconditions	System has trained GRU Autoencoder model Student has at least 10 weeks of behavioural data stored	
Test Steps	Test Input	Expected Results
System retrieves last 10 weeks of student behavioural data	Weekly data (login_count, session_duration, etc.)	Data prepared correctly for model input
GRU model processes sequential data	-	Model calculates reconstruction error
System classifies risk level based on thresholds	Reconstruction error = High	Student classified as HIGH risk
Result stored in database	-	Risk level and error saved with timestamp

Table 3 Test Case2 Reinforcement Learning Intervention Selection

Test Case ID	TC-02	
Test Scenario	RL-based Adaptive Intervention Selection	
Preconditions	GRU model has already generated risk level RL model and Q-table are loaded	
Test Steps	Test Input	Expected Results
System sends current state to RL model	Risk = HIGH, Trend = INCREASING, last_action = REMINDER	-
RL model evaluates state	-	Best action selected
System determines intervention	-	Action = PEER_CHEER or HUMAN_ESCALATION

Action stored in system		Decision saved with reason
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Table 4 Test Case3 Multi-Level Intervention Delivery (Peer & Human Support)

Test Case ID	TC-03	
Test Scenario	Multi-Level Intervention Delivery	
Preconditions	Student identified as HIGH risk RL model selected escalation action	
Test Steps	Test Input	Expected Results
System triggers selected intervention	Action = PEER_CHEER	Peer encouragement message generated
If no response, escalate further	no_response_streak \geq 2	-
System triggers human escalation	Action = HUMAN_ESCALATION	Lecturer/admin notified

3. RESULT AND DISCUSSION

3.1 Results

The implementation of the AcademiGuard system successfully established a scalable and real-time architecture using Firebase as the backend and a FastAPI-based machine learning service. The system was able to process student behavioral data efficiently, enabling continuous monitoring of engagement patterns and timely generation of intervention strategies.

The GRU Autoencoder model was successfully trained and deployed to analyze sequential student behavioral data. Using reconstruction error, the model was able to accurately identify deviations from normal engagement patterns and classify students into different risk levels. The model demonstrated stable performance when tested with real student behavioral datasets, effectively detecting early signs of disengagement.

In addition, the reinforcement learning-based decision engine was integrated successfully with the detection model. The system was able to select appropriate intervention actions based on the current state of the student, including risk level, behavioral trend, and previous interaction history. The intervention mechanism supported multiple actions such as soft nudges, reminders, peer cheer, and human escalation, allowing the system to provide adaptive and context-aware support.

The end-to-end system workflow, from data collection to prediction and intervention delivery, functioned correctly within the required time constraints. The integration between the React frontend, Firebase backend, and FastAPI microservice ensured smooth data flow and real-time responsiveness.

Overall, the system achieved the following:

- Accurate detection of student disengagement using GRU-based sequential analysis.
- Effective selection of personalized interventions using reinforcement learning.
- Successful implementation of a multi-level support system including peer cheer and human support.
- Real-time processing and visualization of student engagement data through dashboards.
- Scalable and secure system performance using cloud-based technologies.

3.2 Research Findings

Evaluation of the system using simulated and real behavioral datasets provided several important findings regarding its effectiveness.

- **Early Detection of Disengagement**

The GRU Autoencoder model was able to identify behavioral changes before they were reflected in academic outcomes. This confirms that sequential pattern analysis is effective for early detection of disengagement.

- **Improved Personalization of Interventions**

The reinforcement learning model demonstrated the ability to adapt intervention strategies based on student behavior. Different students received different actions depending on their engagement level and response history, showing improved personalization compared to static systems.

- **Effectiveness of Multi-Level Support**

The inclusion of peer cheer and human escalation mechanisms improved the overall support structure. Students at higher risk levels received stronger interventions, while low-risk students were not overloaded with unnecessary notifications.

- **Reduced Alert Fatigue**

By selecting actions intelligently, the system avoided excessive notifications. This helped maintain user responsiveness and prevented disengagement from the system itself.

- **Continuous Engagement Monitoring**

The system successfully maintained a continuous record of student behavior, enabling trend analysis over time. This provided valuable insights for both students and lecturers.

3.3 Discussion

The results of this research highlight the importance of moving from traditional reactive monitoring systems to proactive, intelligent engagement support systems. Existing academic monitoring approaches mainly rely on final grades or attendance, which only reflect issues after they occur. In contrast, the proposed system continuously analyses behavioral data and detects disengagement at an early stage.

The use of a GRU Autoencoder model proved effective for capturing temporal patterns in student behavior. Unlike traditional machine learning models, which require labeled data, the unsupervised nature of the autoencoder allows it to detect anomalies based on deviations from normal behavior. This makes it highly suitable for real-world educational environments where labeled disengagement data is limited.

Furthermore, the integration of reinforcement learning introduces a dynamic and adaptive approach to intervention selection. Instead of applying fixed rules, the system learns from previous interactions and continuously improves its decision-making process. This results in more effective and personalized interventions.

An important contribution of this system is the introduction of a multi-level intervention strategy, which includes not only automated notifications but also peer-based support and human involvement. This combination ensures that students receive the appropriate level of support based on their engagement state. In particular, human escalation plays a critical role in handling high-risk cases, where automated interventions alone may not be sufficient.

Overall, the findings demonstrate that integrating behavioral analysis with adaptive intervention strategies can significantly improve student engagement management. By providing early detection, personalized support, and continuous monitoring, the system offers a more effective solution compared to existing approaches. This research confirms that combining deep learning and reinforcement learning within a unified system can create a powerful tool for reducing disengagement and improving academic outcomes in higher education.

4. DESCRIPTION OF PERSONAL AND FACILITIES

Table 5 Description of personal and facilities

Registration No	Name	Task Description
IT22902702	<ul style="list-style-type: none"> • Perera I.A.T.D 	<ul style="list-style-type: none"> • Design and development of the student disengagement detection and intervention system. • Implementation of the GRU Autoencoder model for analysing sequential behavioural data and detecting disengagement patterns. • Development of the Reinforcement Learning model for adaptive intervention selection. • Design and implementation of multi-level intervention strategies including soft nudges, reminders, peer cheer, and human support escalation. • Integration of FastAPI machine learning microservice with Firebase backend and React frontend. • Development of data processing workflow for weekly behavioural data analysis and storage in Firestore. • Design of dashboards and visualization components for displaying engagement trends and risk levels. • Testing, validation, and evaluation of model performance and system functionality.

		<ul style="list-style-type: none">• Preparation of research documentation, report writing, and final project submission.
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APPENDIX

The screenshot shows a Turnitin plagiarism report interface. At the top, the user's name 'Tishan Perera' and document ID 'IT22902702-Final Report' are visible, along with a grade of '-- / 100'. The main content area displays the document title: 'ADAPTIVE AND EXPLAINABLE AI FOR STUDENT RISK PREDICTION AND PERSONALIZED ACADEMIC INTERVENTIONS: A CONTINUOUS LEARNING ANALYTICS FRAMEWORK' and the ID '25-26J-172'. The author's name 'Tishan Dinelka Perera' and document ID '(IT22902702)' are also present. The bottom status bar indicates 'Page 1 of 34', '7067 words', and a zoom level of '180%'. On the right side, a sidebar shows a '9% Overall Similarity' summary with a breakdown: 42 Not Cited or Quoted (9%), 2 Missing Quotations (0%), 0 Missing Citation (0%), and 0 Cited and Quoted (0%). Below this, a 'Not Cited or Quoted' section lists 42 matches from 35 sources, including 'Student papers' (1 match, 2% similarity) and 'Internet' (2 matches, <1% similarity).

Figure 2- Plagiarism Report