Lernpath+: Enhancing Personalized E-Learning Platform

Project ID: R24-112

BSc Special (Hons) - Information Technology

Specialization in Information Technology

Department of Information Technology

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Final Group Thesis

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Declaration, Copyright Statement and The Statement of the Candidate And Supervisor

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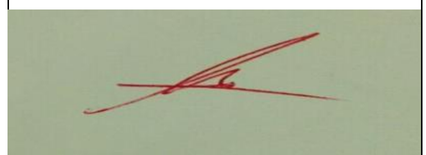
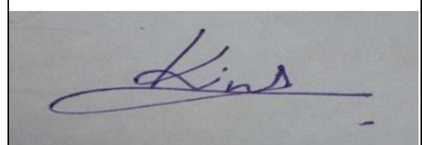
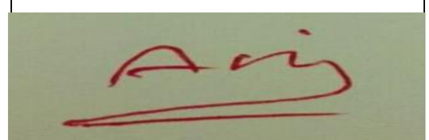
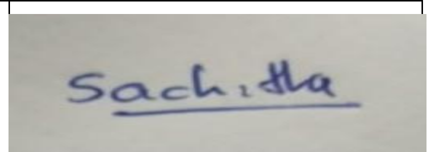
Nishsanka N.A.P.K.R	IT21033032	
Jayasinghe K.A.K.N	IT21032806	
Nishsanka N.A.G.A.A	IT21033974	
Abeykoon R.M.S.P	IT21021602	

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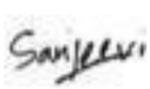

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Ms. Sanjeevi Channdrasiri Date

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ABSTRACT

In In the last few years, the concept of learning that has emerged as a trend is personalized learning, that is, adaptive learning by using artificial intelligence (AI) and machine learning (ML). However, many implemented systems are rather rigid and restrictively designed to offer, besides, learner-irrelevant types of knowledge and learning paths which do not respond to the learner's needs in the course of further usage. The current study aims at highlighting the development of a new adaptive learning environment different from the traditional ones to overcome such shortcomings in as far as cultivating personal learning paths as students learn in real time.

The platform comprises four core components: There are others such as the Student Learning Profiling Module, the Adaptive Recommendation Engine, the Dynamic Learning Pathway Generator as well as a Comprehensive User Interaction and Feedback Loop. The Student Learning Profiling Module involves obtaining quantitative data about learner performance, participation and conduct with a view of constructing an ever-developing database for each learner. This profile is then used by the Adaptive Recommendation Engine to recommend educational content that the student is likely to be at during their learning process so that the recommended content is ever-changing with the progressing knowledge of the student.

The Dynamic Learning Pathway Generator subserves the purpose of extending the framework of personalization of the learning path by dynamically updating the learning path of the student based on real time performance and interaction data. This component guarantees that the learners receive content not too complex but not too simple so that learners work through and stay interested. The Comprehensive User Interaction Feedback Loop is the method by which overall user feedback from the complete interaction process with the system is extracted and used to augment the user profiling as well as the recommendation processes within the system so as to increase the platforms efficiency and accuracy over time.

This was done in all the phases, aiming at the assessment of the performance of each of the main constituents of the research. It became evident when the results showed an increase in concern and attentiveness amongst the students as well as increased retention and enhanced learning as compared to any other format of traditional adaptive learning module. Using real-time data and an ability to modify the learning pathway more frequently the proposed platform is less limited by the problems listed above that current adaptive learning systems suffer from.
This paper discusses how adaptive learning platforms powered by artificial intelligence offer the chance of changing education as we know it by delivering a personalized approach to learning on a case-by-case basis. The dynamic nature of the platform in generating and fine tuning the learning pathway in real time provides a framework, which aspiring e-learning solutions aim to improve by offering a more effective and efficient solution in a large spectrum of learning environments. Subsequent studies will be aimed at the growth of the platform with regard to the number and heterogeneity of learners; as well as the inclusion of the other AI-based learning technologies.

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LIST OF ABBREVIATIONS

Abbreviation	Meaning
AI	Artificial Intelligence
ML	Machine Learning
SLPM	Student Learning Profiling Module
ARE	Adaptive Recommendation Engine
DLP	Dynamic Learning Pathway
DLPG	Dynamic Learning Pathway Generator
CUIFL	Comprehensive User Interaction and Feedback Loop
DL	Deep Learning
ALS	Adaptive Learning System
e-Learning	Electronic Learning
IoT	Internet of Things
NLP	Natural Language Processing
LMS	Learning Management System
HCI	Human-Computer Interaction
ICT	Information and Communication Technology
KPI	Key Performance Indicator
RNN	Recurrent Neural Network
ANN	Artificial Neural Network
SVM	Support Vector Machine
RL	Reinforcement Learning
CNN	Convolutional Neural Network
API	Application Programming Interface
UI	User Interface

UX	User Experience
AR	Augmented Reality
VR	Virtual Reality
IEEE	Institute of Electrical and Electronics Engineers
GPU	Graphics Processing Unit
SaaS	Software as a Service
PaaS	Platform as a Service
BaaS	Backend as a Service
NIST	National Institute of Standards and Technology
WBS	Work Breakdown Structure

1. INTRODUCTION

1.2. Background & Literature Survey:

The education sector has been through key changes bearing in mind the current introduction of the technological innovations in learning. With more students out there who do not fit to the traditional one size, one approach system of learning, it has become harder to cater for all the students hence the development of adaptive learning systems. Such systems use AI and ML technologies to adapt the content to students and their responses, and further more rely on the responses given by the newcomer.

Past researches have pointed out that tailored instruction is essential for increases in students' performances. Research proves that when the delivery of the content is done with the help of adaptive learning platforms, the engagement, retention as well as the knowledge retention goes up significantly [1]. However, there are several, if not many, learning systems with an adaptive version, which can be often problematic for providing timely changes of the learning paths in line with student progress and/or reviews.

For instance, the first forms of adaptive learning models including Intelligent Tutoring Systems (ITS) and Massive Open Online Courses (MOOCs) tried to integrate triune parameters of personal learning but most of them did not have the feedback mechanism that can change the learning paths constantly. Most of these models therefore incorporate pre-specified pathways or feedback cycles, which restrict the models evolution as students advance through different stages of learning [2].

Adaptive learning has evolved over time and with the current research presented here a new dynamic adaptive system is added in which the learner data and the model is updated dynamically and the learning is personalized for the initial data of the student as well as the dynamic data of an adaptive learner. The envisioned system is to incorporate dynamic learning paths and feedback loops which will then make the learning process more flexible and engaging and assist students gain improved results due to delivery of pertinent material at profitably timed intervals.

1.2. Research Gap:

While much has been written about the use of adaptive learning, there is still a dearth of research on the development of learning paths that adapt over time and in real-time. Some are even predicted, which in simple terms makes a learner's development path predetermined at the start and allows limited man oeuvre as the learner proceeds through their chosen path. This form of organization does not consider periods of variation in a student's understanding, attentiveness, or require a review or a higher level of learning at moments.

Furthermore, the concern has been voiced about the absence of broad and efficient and effective schemes for incorporating interaction with the users and assessment of their feedback into the learning process. Existing models are generally one-way and feedback is kept to a simple form of performance check such as test results or completion of assigned tasks. Very few of the current systems can utilize real-time data found in pattern of interactions or levels of engagement to modify content delivery instantly.

Albeit a great progress has been made advancing the employments of adaptive learning technologies adapting in helping students customize their learning, it is important to note, that a major break has not been filled in the identification of more progressive adaptive learning paths. Modern forms of adaptive learning are typically linear and course-based or at least rigidly pre-structured, so that the path of a learner is set prior to the beginning of his education process. This approach may be somewhat restrictive because it fails to capture the dynamic nature of the process of student learning – fluctuations in the level of interest or comprehending of a material, as well as changing requirements, among other things. They do not adapt to situations where understanding might be low, attention might be low, or when students require a revisit of previous material or material that is more complex as they advance in their learning.

Furthermore, there is also the problem of absence of substantial and efficient approach in the question of how to implement user interactivity and feedbacks into the adaptive learning process. Current models are primarily autocratic in that feedback provided is rather in terms of a performance, an examination score or the completion rate of tasks. This approach fails to take advantage of the possibility of using real-time data of interaction to optimize content delivery. Almost no system is designed to capture real-time patterns of students' involvement and communication to tailor the learning process on the fly [3].

This research will seek to fill these gaps by developing an adaptive learning system, which will be in three tiers and posited to provide learning solutions in real-time and with feedback from the learner. The proposed system will consist of: The proposed system will consist of:

- ✓ **Real-Time Student Portrayal:** A part of the student record that instantly tracks the student academic outcomes, conduct and activity, and gives the complete picture of the current state of the learner.
- ✓ **Dynamic Recommending System:** A real-time learning facilitative mechanism which automatically synchronizes the learning recommendations with the identification and evaluation of the learner's real-time performance data.
- ✓ **Learning Path Construction Mechanism:** A flexible development tool that use a student's interactions and performance to tailor the learning process in a way that allows for changes in the learning path as needed.

With such form of a system that infuses feedback and behaviors in real-time, the idea is to create a soon rather than later system that modifies the learning path as well as the feedback mechanism, which is, at the moment, linear and strictly defined.

This research seeks to fill these gaps by proposing a three-tier adaptive learning system which includes real time student portrayal, a dynamic recommending system and a learning path construction mechanism. The system is to be developed with the ability to process not only the student's academic performance but also the behavior and interaction data that the system is to collect and display to facilitate a more effusive student experience.

1.3. Research Problem:

The problem that this research aims to solve is the lack of fully real-time adaptive learning environments which must be capable of improving the contents delivered by the system based on feedback received after the delivery. While conventional methods of individualized learning has its advantages, it tends to suffer from conventional adaptation models that cannot elaborate on the differences and changes in learners' processes. Inadequate in their capacity to recognize and address the variety and dynamism of learning needs that perforce makes the needs of the students mismatch those of a system perpetuated by these static models.

Often, the current forms of personalized learning depend on the historical data and the set learning patterns; this is because many of them can only make recommendations based on previous sessions or predefined patterns. Consequently, such systems do not do well in regard to accommodating the dynamics of actions in real-time and student behavioral learning patterns. This results in a critical failure regarding the student's ad hoc needs; education is not sufficiently tailored as needed.

The essence of this research problem resides in the need for a system that would not merely rely on the statistics retrieved from previous tests, but would rather receive the real-time feedback and adapt the learning content and approach on the fly. Such dynamic response could lead to more appropriate and efficient educational support to the learners and so, could positively affect their learning experience [4].

This research, therefore, intends to fill this gap by designing a system that does not only depend on the history of the student's performance but also adjusts in real-time given the student's conduct and learning ability. Through the use of real time analysis and learning adaptation, the proposed system intended to develop a more dynamic learning environment. This system would modify the learning track depending with the current interactions, meaning that the educational process would be a lot more relevant to a students' needs and behavior patterns as compared to the set patterns of the normal classroom structure. Thus, this research was intended to contribute to marking the progress and individualization of the contemporary educational technologies.

1.4.Objectives:

1.4.1. Main Objective:

The main reason for this research is to design and implement an adaptive learning system with the ability to create a new learning path for the student based on the student's learning style, a recommendation system, and feedback loop. The proposed system will be a more efficient method of student interaction and learning because the system will constantly update the format of learning depending on the overall performance, interactions, and feed-back received in the process.

1.4.2. Specific Objectives:

- **Develop a Student Learning Profiling Module:** This module shall contain—real time—information about students' performance, participation, and conduct; the profiles are dynamic and update in response to changing information. The profile that will be created will be used to make recommendation of learning and changes to pathways where necessary.
- **Implement an Adaptive Recommendation Engine:** It will be an engine that will derive the educational content for the student based on a profile created for the student. The engine will employ the machine learning algorithms to mean that the recommended content will meet the student's current need, challenge, and gaps.
- **Create a Dynamic Learning Pathway Generator:** This component will dynamically create and update learning pathway that will always reflect real-time data. The generator will modify the path that the student follows in their learning process so to keep the material relevant and engaging and on target with what the goal of the student is.
- **Integrate a Comprehensive User Interaction and Feedback Loop:** The performance of the system will be also in a position to gather reflection on the specific user interactions and incorporate it into the generation of the learning pathways. These are the feedbacks through which it would be possible to make the recommendations and pathways more accurate in the future and to make learning process more adaptive [5].

2. METHODOLOGY

As discussed in this section, it explains the approach that has been employed in the design, development and evaluation of the adaptive learning platform. The methodology is structured around the design and implementation of four key system modules: thus the Student Learning Profiling Module; the Adaptive Recommendation Engine; the Dynamic Learning Pathway Generator; and the Comprehensive User Interaction and Feedback Loop. The concept of these modules is to connect them and create an adaptive artificial intelligence-based learning environment that adapts the educational material according to the obtained data.

2.1. System Architecture

The system is modular with specific links between parts, based on the existence of a central data processing unit. All of them have their role in the broader set of adaptive learning framework, which in turn must create a unified and coherent system meant to improve the educational process through the means of individualization [6]. This following sub-section is a detailed description of each of the modules implemented:

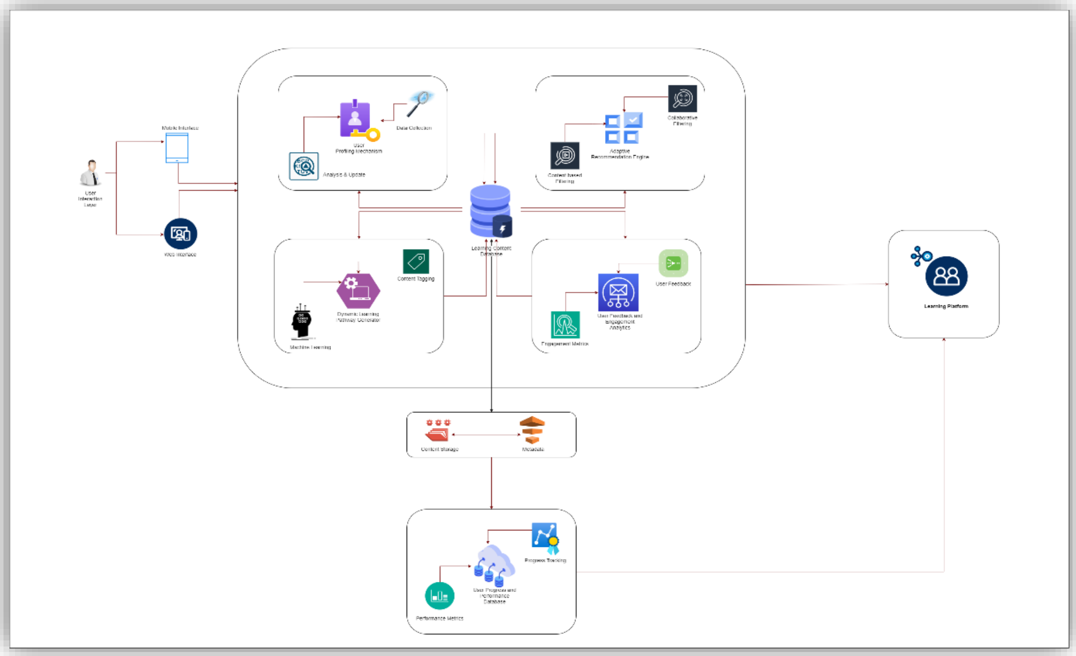

Figure 1: Overall System Diagram

2.1.1. Student Learning Profiling Module:

The Student Learning Profiling Module is the basis for the learning process that is based on the collection and analysis of data on the learning behaviors, performance indicators and communication patterns of the student.

- **Data Collection:** The data sources include the assessments such as quizzes, exams, assignments and behavioral data at the moment as defined by the click stream data, time spent on the activity as well as interaction with multimedia. The general and specific interactions, as well as other measures which concern the amount of engagement, accuracy, speed and understanding of the information, are all gathered to develop an adequate picture of the student's learning profile.
- **Profile Development:** Based on data received the system then reconstructs the current state, which will comprise the level of knowledge of the student, the ways that are more effective for the receipt of information (visual, auditory, or physical), as well as those lessons that are problematic or easy for the student. This profile may be dynamic in nature and changes with the collection of more data by the system about the particular learner.
- **Machine Learning Integration:** The profiling module involves of the machine learning methods to analyze and give patterns of student behaviors and performance. These patterns affect the performance of the system itself and provides the capability to further predict

performance in order to maintain control and make alterations to the learning path when necessary.

- **Data Processing:** Some of the Data Processing Methods applied to the interactions students have with materials include Natural Language Processing (NLP) and Predictive Modelling, which AUT generates into insights for the ARP [7].

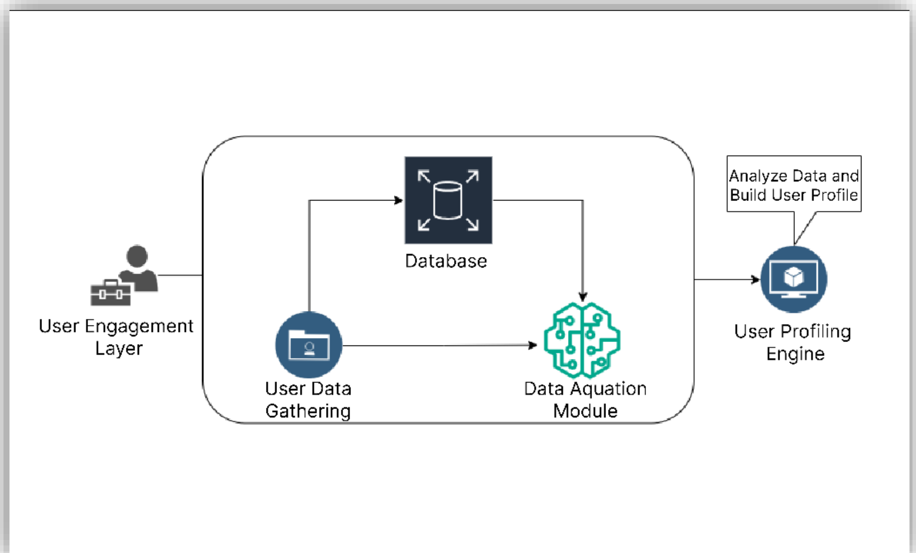

Figure 2: Student Learning Profiling Module-Component Diagram

2.1.2. Adaptive Recommendation Engine:

The are is charged with the responsibility of recommending content based on the progressive profile of the student. It helps to make sure that the learner is provided with items that are commensurate with a learner's current ability, but which are nonetheless demanding enough to encourage a learner to progress [8].

- **Algorithm Design:** The recommendation engine uses collaborative filtering, content-based filtering, and reinforcement learning algorithms to suggest educational resources. Collaborative filtering takes into account the preferences and behaviors of other similar learners, while content-based filtering focuses on the specific attributes of the learning materials (difficulty, subject matter, format) and how they match the learner's profile.
- **Real-time Adjustment:** Real-time performance of the engine is used, which depends on the student's activities and the received feedback at the moment. For instance, if a student fails to grasp some lesson or material, the engine will provide another resource or slows down the lesson delivery to assist the student.

- **Content Personalization:** The stated source of the engine is diverse type of material what comprises videos, reading, quizzes, and various exercises touching education. Each resource includes tags referring to difficulties, topics and formats; therefore the system is able to provide the client with a selection of relevant data.
- **Feedback Integration:** Embedded into the engine also, is the real-time feedback of the student's activity with content like completion rates, time on a task, quiz results to name but a few; it is through such metrics that recommendations are further tuned.

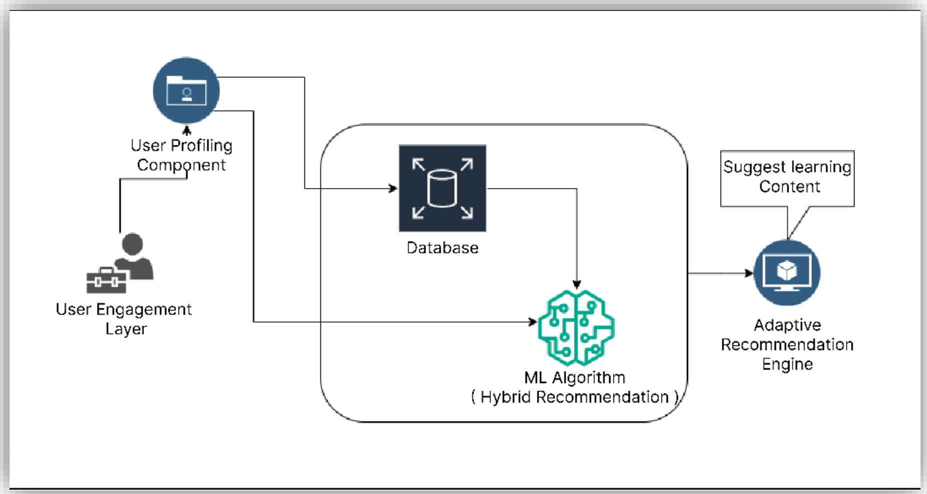

Figure 3: Adaptive Recommendation Engine-Component Diagram

2.1.3. Dynamic Learning Pathway Generator:

The Dynamic Learning Pathway Generator is based upon the suggestions given by the Adaptive Recommendation Engine to offer a progressive learning plan that may change on the basis of the results of the students' activity.

- **Pathway Design:** This component develops learning tracks that organize learning material in a way that gives better results for the student in question. These are not 'vertical' pathways, which make a student's move forward, but more like a spiral, giving a student the opportunity to revisit and repeat something as many times as is needed before they progress to the next level once they are ready.
- **Real-time Adjustments:** The performance of a student throughout the pathway is tracked and the pathway itself changes its course depending on the student trends. For instance, if a student masters content within a short time, the pathway generator can advance the student to higher challenging content. On the other hand if a student is lagging, the pathway will circulate back to mastery or offer resources that the student may need to refresh on.

- **Adaptive Sequencing Algorithms:** The pathway generator then uses the concept of adaptive sequencing where learning content to be shown to the student is based on his/her progress, feedbacks, accesses, and more. Such algorithms makes the learning pathway adaptive so that it can shift as and when as per the learner's needs are evolving [9].
- **Modular Pathway Development:** The pathways are organized in a flexible manner fo matter what the criterion can be students' learning objectives, time and or learning preference. It is meant not only for achieving target short-term objectives, such as learning specific information or a topic (e. g. , a particular concept), but also for attaining long-term educational aims, for instance, accomplishing a course or studying a curriculum.

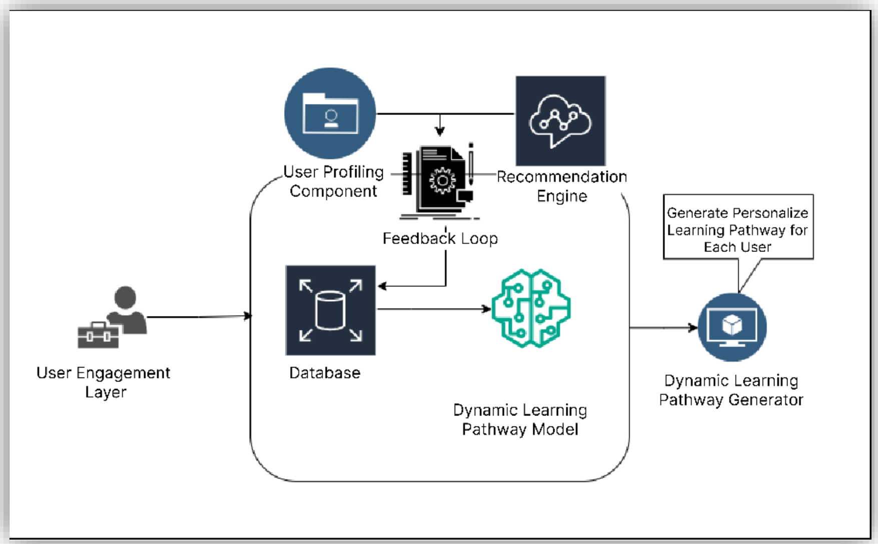

Figure 4: Dynamic Learning Pathway Generator-Component Diagram

2.1.4. Comprehensive User Interaction and Feedback Loop:

Another important component is the analysis of the result of Pedagogy system interaction with the user: the student and the ability to develop a detailed feedback loop concerning the development of the student's profile and the learning path.

Feedback Collection: The system obtains direct feedback from the students in the form of questionnaires, tests, and assignments; indirect feedback is also collected based on the generation of the behaviors of students such as engaged time, time spent for each activity, time spent on multimedia etc. Such multi-dimensional feedback is apparently very important for bringing changes in the system in real-time.

- **Behavioral Analytics:** The feedback loop works based on the sophisticated behavior analysis of how students engage with the platform. For example, if a student is absentminded and does not attend particular kinds of content (for example, videos), the system will change a learning route to include more of the materials this kind of student prefers (for example, readings or quizzes).

- **Continuous Adaptation:** The feedback loop ensures that the system evolves with time so as to suit each learner, based on their learning style. Every time data is fed back, into both the Student Learning Profiling Module and the Adaptive Recommendation Engine, the system gets better at predicting the learner's needs and the routes charted for her.
- **User-Centric Improvements:** Feedback loop also helps in system improvement through analysis of results for a plurality of clients. All these assist in updating the existing algorithms used in the system, to modify the educational content, and to optimize the user experience of the system.

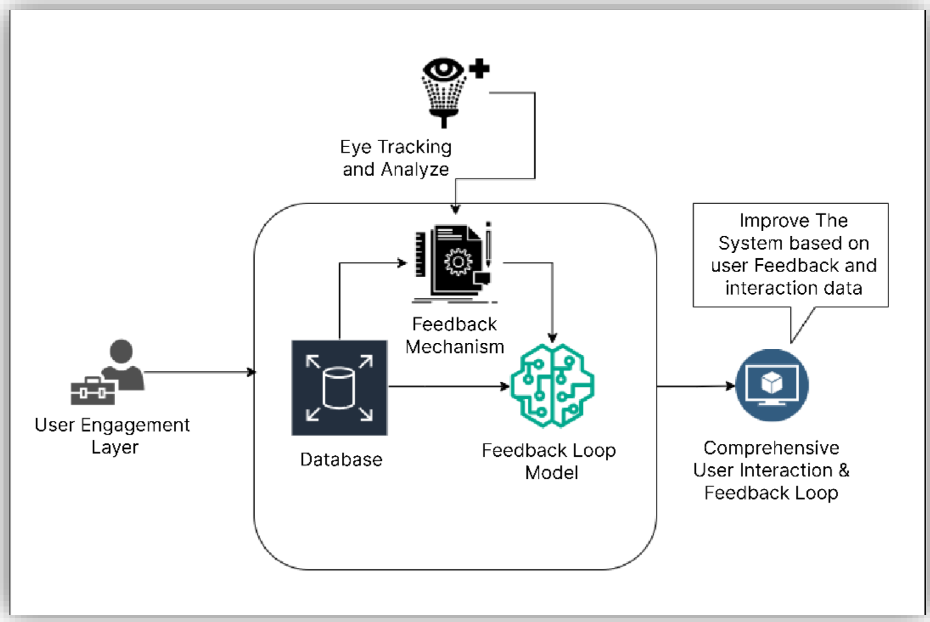

Figure 5: Comprehensive User Interaction and Feedback Loop-Component Diagram

2.2 Implementation Strategy:

The system was created in stages, each stage having its own module, which was tested before the incorporation of the other. Modular development ensured that each component can work as expected for a certain period before integrating it with the other components to form a large and complex system. Refinement that occurred comprised of testing of the implemented procedures and feedback incorporation to improve the overall functionality of the platform [10].

2.2.1. Data Collection and Management:

A lot of data was captured during execution of the tests to enhance the stability of the profiling and recommendation That was done to avoid disclosing the identity of the students and maintain the privacy and security of the data in compliance with the educational data practices act and the family educational rights and privacy act.

	A	B	C	D	E	F	G	H	I	J	K
1	Proficiency le	Preferred subje	Preferred stuc	Goals	Quiz scores	Completion	Time spent on	Curriculum stru	Available content	External factors	Learning style
2	Low	Software	Morning	Short-term	1	1	1	Exam	Lectures	Time Constraints	Visual
3	Low	Software	Morning	Short-term	1	2	2	Knowledge	Quiz	Time Constraints	Visual
4	Low	Software	Morning	Short-term	1	3	3	Exam	Quiz	Time Constraints	Visual
5	Low	Software	Morning	Short-term	1	4	4	Knowledge	Quiz	Time Constraints	Visual
6	Low	Software	Morning	Short-term	1	5	5	Exam	Quiz	Time Constraints	Visual
7	Low	Software	Morning	Short-term	1	6	6	Knowledge	Quiz	Time Constraints	Visual
8	Low	Software	Morning	Short-term	1	7	7	Exam	Quiz	Time Constraints	Visual
9	Low	Software	Morning	Short-term	1	8	8	Knowledge	Quiz	Time Constraints	Visual
10	Low	Software	Morning	Short-term	1	9	9	Exam	Quiz	Time Constraints	Visual
11	Low	Software	Morning	Short-term	1	10	10	Knowledge	Quiz	Time Constraints	Visual
12	Low	Software	Morning	Short-term	1	1	11	Exam	Quiz	Time Constraints	Visual
13	Low	Software	Morning	Short-term	1	2	12	Knowledge	Quiz	Time Constraints	Visual
14	Low	Software	Morning	Short-term	1	3	13	Exam	Quiz	Time Constraints	Visual
15	Low	Software	Morning	Short-term	1	4	14	Knowledge	Quiz	Time Constraints	Visual
16	Low	Software	Morning	Short-term	1	5	15	Exam	Quiz	Time Constraints	Visual
17	Low	Software	Morning	Short-term	1	6	16	Knowledge	Quiz	Time Constraints	Visual
18	Low	Software	Morning	Short-term	1	7	2	Exam	Quiz	Time Constraints	Visual
19	Low	Software	Morning	Short-term	1	8	2	Knowledge	Quiz	Time Constraints	Visual
20	Low	Software	Morning	Short-term	1	9	2	Exam	Quiz	Time Constraints	Visual
21	Medium	Software	Morning	Short-term	1	10	8	Knowledge	Quiz	Time Constraints	Visual
22	Medium	Software	Morning	Short-term	1	1	8	Exam	Quiz	Time Constraints	Visual

Figure 6: Sample Dataset - Use for DLPG Model Train (5000 It Student Data Set)

2.2.2. System Integration:

Four fundamental modules are under the DM, and all these were designed to work in a parallel processor fashion with the central data processing unit serving to coordinate the flow between the modules. To promote scalability, a cloud-based infrastructure was implemented to make certain that the system could accommodate multiple users concurrently it is composed of.

```
# Train the model for predicting Complexity
model_complexity = RandomForestClassifier(random_state=42)
model_complexity.fit(X_train_complexity, y_train_complexity)

# Make predictions and evaluate the model
y_pred_complexity = model_complexity.predict(X_test_complexity)
print("Accuracy for 'Complexity':", accuracy_score(y_test_complexity, y_pred_complexity))
print("Classification Report for 'Complexity':\n", classification_report(y_test_complexity, y_pred_complexity))

# Save the model and label encoders
joblib.dump(model_complexity, 'model_complexity.pkl')
joblib.dump(label_encoders, 'label_encoders.pkl')
joblib.dump(scaler, 'scaler.pkl')
```

```
Accuracy for 'Complexity': 1.0
Classification Report for 'Complexity':
              precision    recall  f1-score   support

    Advanced       1.00      1.00      1.00       248
    Beginner       1.00      1.00      1.00       926
Intermediate       1.00      1.00      1.00       368

    accuracy                           1.00      1542
   macro avg       1.00      1.00      1.00      1542
weighted avg       1.00      1.00      1.00      1542

['scaler.pkl']
```

Figure 7: Student Learning Profiling Module and Its Accuracy

```python
@app.route('/predict', methods=['POST'])
def predict():
    # Get the JSON data from the request
    data = request.json

    # Create a DataFrame from the input data
    input_data = pd.DataFrame([data])

    # Encode categorical variables
    categorical_cols = ['Subject']
    for col in categorical_cols:
        input_data[col] = label_encoders[col].transform(input_data[col])

    # Standardize numerical features
    numerical_cols = ['Course Score', 'Learning Score', 'Quiz Score']
    input_data[numerical_cols] = scaler.transform(input_data[numerical_cols])

    # Predict the Complexity
    complexity_prediction = model_complexity.predict(input_data)

    # Predict the Learning Content
    content_prediction = model_content.predict(input_data)

    # Create the response dictionary
    response = {
        'Predicted Complexity': complexity_prediction[0],
        'Predicted Learning Content': content_prediction[0]
    }

    return jsonify(response)

if __name__ == '__main__':
    app.run(debug=True)
```

Figure 8: SLPM - Using Model Implement Flask API

```python
# Initialize the model
model = RandomForestClassifier(random_state=42)

# Train the model
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)
```

Figure 9: ARE - Model (random forest)

```python
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")

# Print classification report
print(classification_report(y_test, y_pred))

# Optional: Confusion matrix
print(confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.99
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        82
           1       1.00      0.96      0.98        95
           2       1.00      1.00      1.00        85
           3       1.00      0.98      0.99        84
           4       1.00      1.00      1.00        84
           5       1.00      1.00      1.00        78
           6       0.96      1.00      0.98       297
           7       1.00      0.96      0.98        76
           8       1.00      0.96      0.98        91
           9       1.00      1.00      1.00        40

    accuracy                           0.99      1012
   macro avg       1.00      0.99      0.99      1012
weighted avg       0.99      0.99      0.99      1012
```

Figure 10: ARE - Model accuracy

```python
@app.route('/predict', methods=['POST'])
def predict():
    try:
        # Get the data from the request
        data = request.json
        subject = data['subject']
        course_score = data['course_score']
        learning_score = data['learning_score']
        quiz_score = data['quiz_score']

        # Transform the categorical input
        subject_encoded = label_encoder_subject.transform([subject])[0]

        # Create DataFrame for the new data
        new_data = pd.DataFrame([[subject_encoded, course_score, learning_score, quiz_score]],
                                columns=['Subject', 'Course Score', 'Learning Score', 'Quiz Score'])

        # Scale the features
        new_data[['Course Score', 'Learning Score', 'Quiz Score']] = scaler.transform(new_data[['Course Score', 'Learning Score', 'Quiz Score'

        # Make prediction
        prediction_encoded = model.predict(new_data)

        # Transform the prediction back to text
        recommendation = label_encoder_recommendation.inverse_transform(prediction_encoded)

        return jsonify({'recommendation': recommendation[0]})

    except Exception as e:
        return jsonify({'error': str(e)}), 400

if __name__ == '__main__':
    app.run(debug=True)
```

Figure 11: ARE - Using Model Implement Flask API

```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout

# Define the neural network model
model = Sequential([
    # Input layer with 10 nodes
    Dense(128, activation='relu', input_shape=(10,)),
    Dropout(0.5),
    Dense(64, activation='relu'),
    Dropout(0.5),
    # Output layer with appropriate activation function
    Dense(3, activation='softmax')  # Assuming 3 classes for the output
])

# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',  # Use sparse categorical crossentropy for integer labels
              metrics=['accuracy'])
```

Figure 12: DLPG - Model (CNN)

```python
import numpy as np

# Evaluate the model on the test set
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print("Test Accuracy:", test_accuracy)
```

```
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9732 - loss: 0.0961
Test Accuracy: 0.9700000286102295
```

Figure 13: DLPG - Model Accuracy

```python
# Define a route for prediction
@app.route('/predict', methods=['POST'])
def predict():
    # Get data from the request
    input_data = request.json

    print(input_data)

    # Preprocess input data for testing
    preprocessed_input = preprocess_input(input_data)

    # Make predictions using the trained model
    predictions = model.predict(preprocessed_input)

    # Get the predicted class
    predicted_class_index = np.argmax(predictions)
    predicted_class = label_encoder_Y_classes.classes_[predicted_class_index]

    # Return the predicted class
    return jsonify({'predicted_class': predicted_class})

if __name__ == '__main__':
    app.run(debug=True)
```

Figure 14: Using DLPG Model Implement Flask API

```python
model = tf.keras.models.Sequential([
    Input(shape=(64, 64, 3)),

    Conv2D(filters = 32, kernel_size = 5, strides = 1, activation = 'relu'),
    Conv2D(filters = 32, kernel_size = 5, strides = 1, activation = 'relu', use_bias=False),
    BatchNormalization(),
    MaxPooling2D(strides = 2),
    Dropout(0.3),

    Conv2D(filters = 64, kernel_size = 3, strides = 1, activation = 'relu'),
    Conv2D(filters = 64, kernel_size = 3, strides = 1, activation = 'relu', use_bias=False),
    BatchNormalization(),
    MaxPooling2D(strides = 2),
    Dropout(0.3),

    Flatten(),
    Dense(units  = 256, activation = 'relu', use_bias=False),
    BatchNormalization(),

    Dense(units = 128, use_bias=False, activation = 'relu'),

    Dense(units = 84, use_bias=False, activation = 'relu'),
    BatchNormalization(),
    Dropout(0.3),

    Dense(units = 1, activation = 'sigmoid')
  ])
```

Figure 15: CUIFL - Model (CNN)

```python
from keras.models import load_model
best_model = load_model('C:/Users/Kishan raj/Documents/GitHub/EduQuest/eye_track/prediction.keras')
best_model.evaluate(x_test, y_test)
```

```
9/9 ━━━━━━━━━━━━━━━━━━━━ 1s 41ms/step - accuracy: 0.7635 - loss: 0.3055

[0.31147608160972595, 0.7451737523078918]
```

Figure 16: CUIFL - Model Accuracy

```python
# Initialize video capture from webcam
cap = cv2.VideoCapture(0)  # Change the index if you have multiple webcams

while True:
    # Capture frame-by-frame
    ret, frame = cap.read()

    # Convert OpenCV image (numpy array) to PIL image
    pil_img = Image.fromarray(cv2.cvtColor(frame, cv2.COLOR_BGR2RGB))

    # Predict using the loaded model
    prediction = predict_image(pil_img)

    # Display the prediction result
    if prediction > 0.5:
        cv2.putText(frame, 'Focus', (50, 50), cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 255, 0), 2, cv2.LINE_AA)
    else:
        cv2.putText(frame, 'Non Focus', (50, 50), cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 0, 255), 2, cv2.LINE_AA)

    # Display the resulting frame
    cv2.imshow('Frame', frame)

    # Break the loop when 'q' is pressed
    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

# Release the capture
cap.release()
cv2.destroyAllWindows()
```

Figure 17: Using CUIFL Model Implement Flask API

2.2.3. User Interface Design:

Navigational paradigms were developed so as to enable easy orientation by the students to their learning maps their course content and feedback. The interface of the course was tested for ease of use and general accessibility to all possible clients.

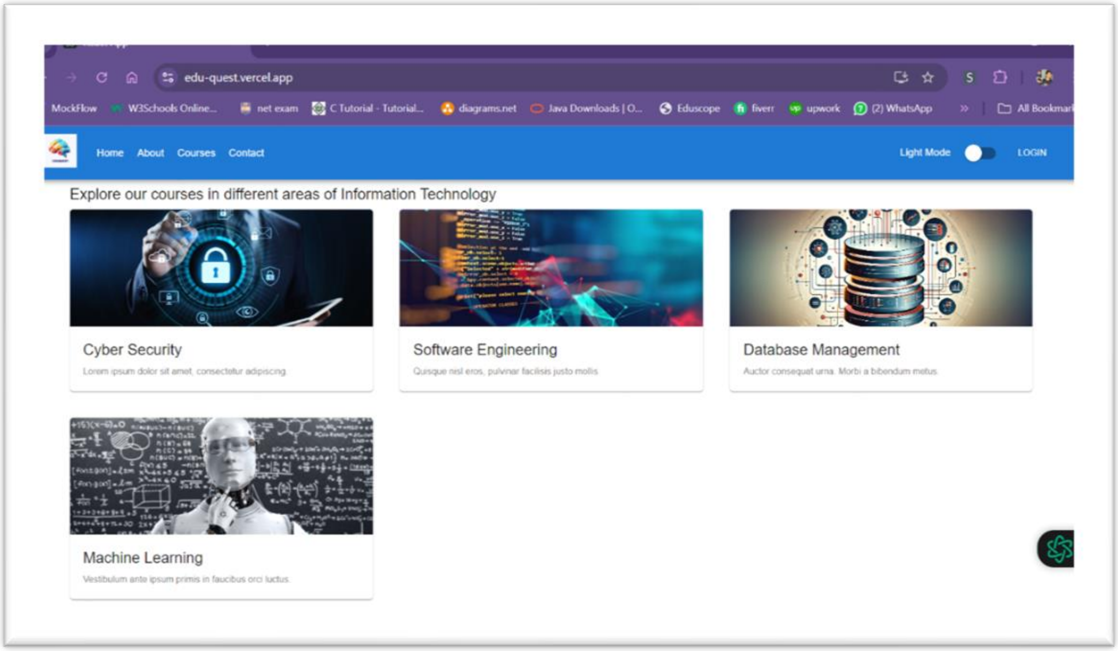

Figure 18: Sample Front-end - Dashboard

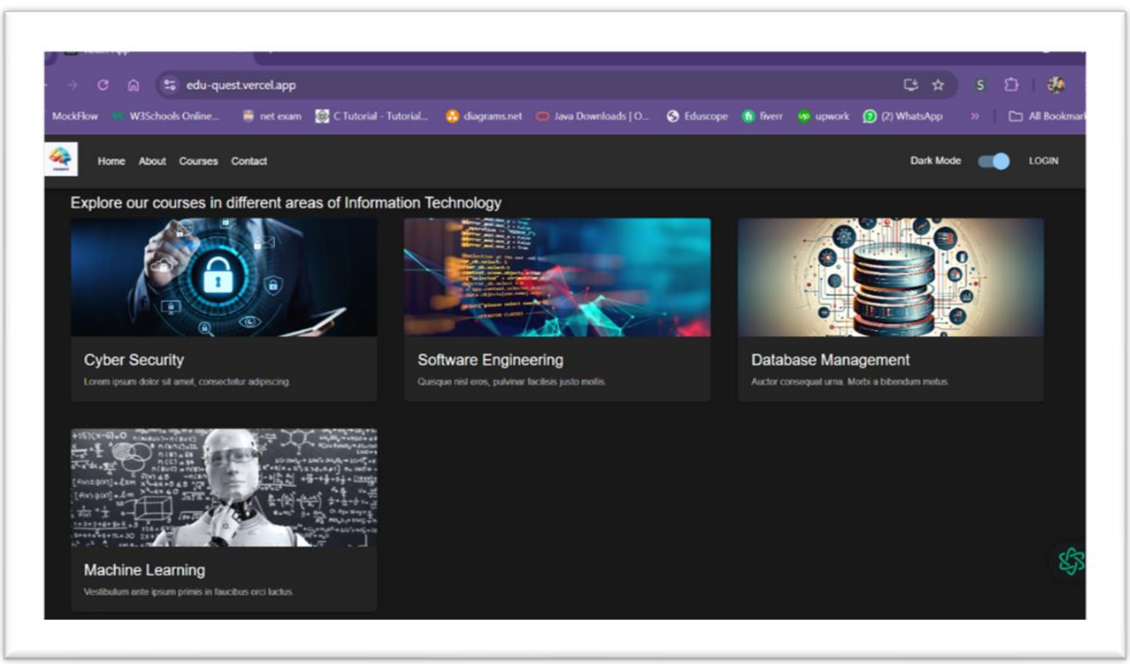

Figure 19: Front-End Dark Mode Active (UX)

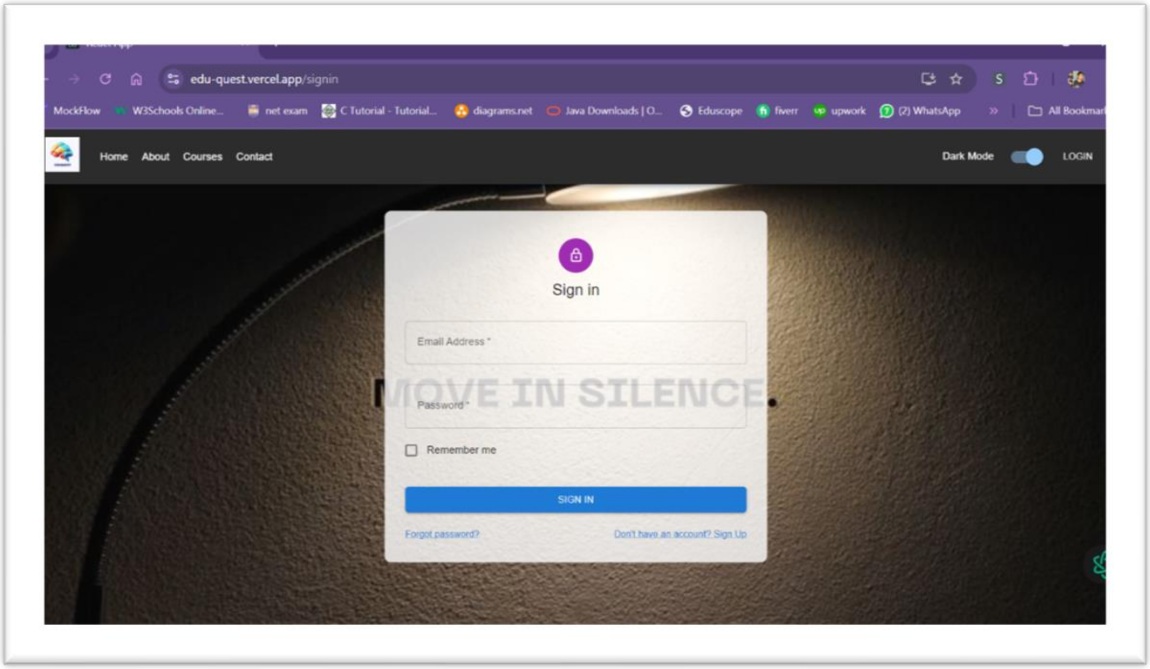

Figure 20: Sign In Interface

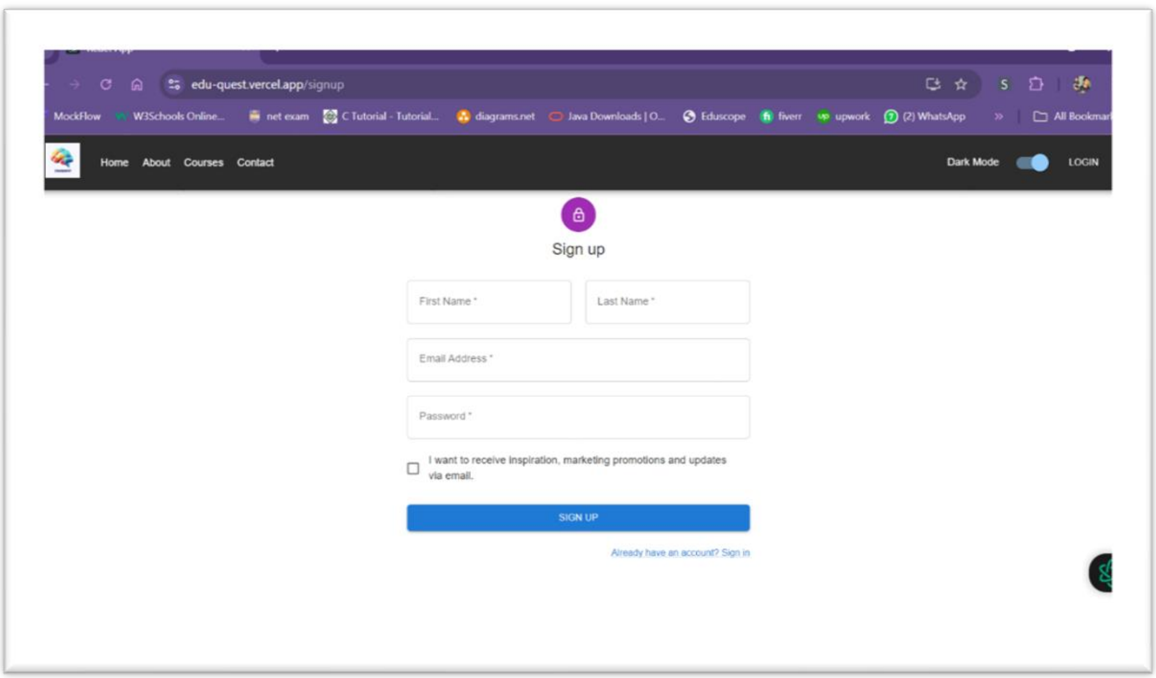

Figure 21: Sign Up Interface

Figure 22: Mobile Responsive Frontend

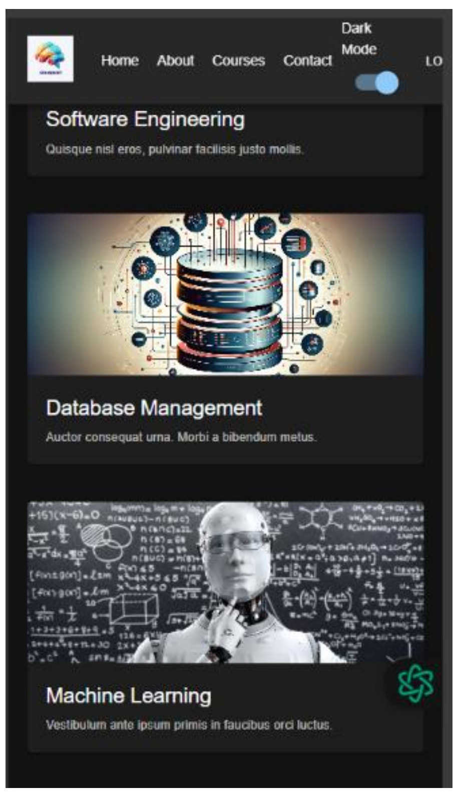

Figure 23: Mobile Responsive Frontend- Sample 2

3. TESTING

The testing phase is an important stage of the system's verification; it cements the belief that every module will work as planned and will be capable of providing the right, timely and unique learning content [11]. This section provides an overview of the testing process and the test outcomes for each of the fundamental interface elements, together with particular test samples shown in tabular format to demonstrate some of the primary testing situations.

3.1. Student Learning Profiling Module

Objective:

To verify the effectiveness of data acquisition, updates of the students' profile information, and the outcomes of the learning algorithms embodied in the Student Learning Profiling Module.

Testing Methodology:

White box testing in the form of unit tests and black box testing in form of integration tests were used to check how well the profiling module works especially on aspects such as data accuracy, frequency of profile update, and machine learning models on the probability of successful course completion amongst students [12].

Test Case	Description	Test Data	Expected Result
Data Collection Accuracy	Verify accurate collection of performance and behavioral data.	Simulated student interaction data (quiz scores, task completion times).	Data is captured accurately and stored in the correct fields without loss or distortion.
Profile Update Mechanism	Ensure dynamic updates to student profiles as new data is received.	Progressive test data showing student performance changes over time.	Student profiles dynamically reflect evolving performance metrics and engagement data.
ML Model Accuracy	Validate the prediction accuracy of machine learning algorithms.	Historical and current performance data.	Machine learning models predict future performance trends with high accuracy.
Behavior Analysis Accuracy	Confirm system's ability to identify patterns in student behavior and adjust profiles.	Simulated behavior data (e.g., repeated interaction with specific content types).	The system accurately identifies patterns and adjusts student profiles based on detected behaviors.

Table 1: SLPM Test Case

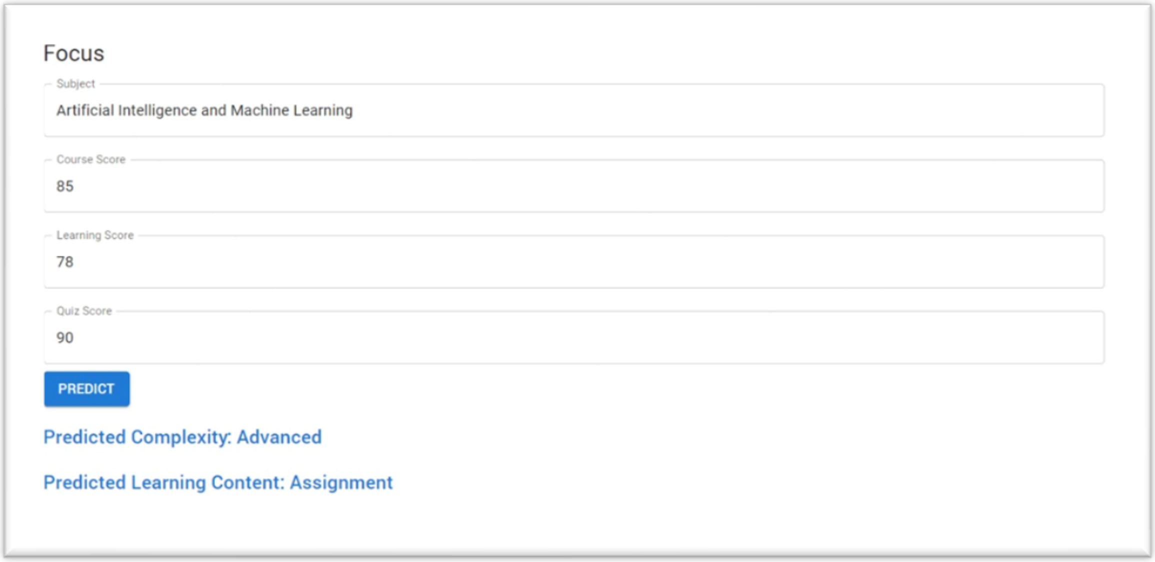

Figure 24: Results Were Checked from Frontend and Got the Outputs (SLPM)

```python
# URL of the Flask API
url = 'http://127.0.0.1:5000/predict'

# Example input data
data = {
    'Subject': 'Artificial Intelligence and Machine Learning',
    'Course Score': 85,
    'Learning Score': 78,
    'Quiz Score': 90
}
```

Figure 25: Set the Testing Values and URL for Testing (SLPM)

```
TERMINAL   PORTS   JUPYTER   PROBLEMS   OUTPUT   DEBUG CONSOLE
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest> cd pathway
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest\pathway> python app.py
 * Serving Flask app 'app'
 * Debug mode: on
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
 * Restarting with stat
 * Debugger is active!
 * Debugger PIN: 146-068-290
```

Figure 26: App Running Successfully (SLPM)

```
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest\pathway> python test.py
{'Predicted Complexity': 'Advanced', 'Predicted Learning Content': 'Assignment'}
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest\pathway>
```

Figure 27: Result For Tested Values (SLPM)

3.2. Adaptive Recommendation Engine

Objective:

To further evaluate the recommendation engine and its performance of providing student learning recommendations depending on the current student profile and the changes in the further learning process.

Testing Methodology:

Unit testing as well as system level testing were both performed in establishing the recommendation engine. Substantial emphasis was placed on the effectiveness of algorithms in different situations, conformity with the desired parameters, and the speed of calculations made [13].

Test Case	Description	Test Data	Expected Result
Recommendation Accuracy	Ensure accurate recommendations tailored to the student's learning profile.	Profiles with different levels of mastery in various subjects.	Recommendations match the student's current learning level and preferences.
Adaptability of Recommendations	Test engine's real-time adaptation based on student performance changes.	Simulated performance data changes.	Recommendations adjust in real-time, providing remedial or advanced material as needed.
Collaborative Filtering Performance	Validate content recommendations based on similar students' learning patterns.	Dataset of student profiles with similar learning patterns.	The engine provides appropriate content based on collective preferences and outcomes of similar students.
Reinforcement Learning Efficiency	Test engine's ability to optimize recommendations based on feedback.	Simulated feedback loops (positive and negative).	Future recommendations adjust based on prior feedback to better suit student preferences.

Table 2: ARE Test Case

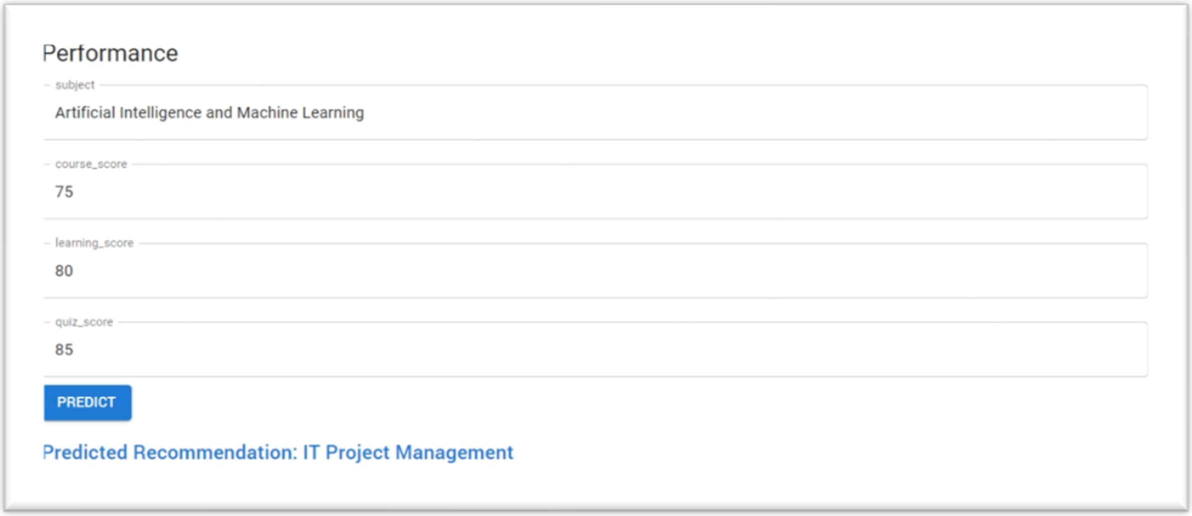

Figure 28 : Inputs were passed to the URL and the outputs were received (ARE)

```python
# Define the URL of the Flask API
url = 'http://127.0.0.1:5000/predict'

# Define the input data
input_data = {
    'subject': 'Artificial Intelligence and Machine Learning',
    'course_score': 75,
    'learning_score': 80,
    'quiz_score': 85
}
```

Figure 29: Set the Testing Values and URL for Testing (ARE)

```
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest> cd .\recommend\
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest\recommend> python .\app.py
 * Serving Flask app 'app'
 * Debug mode: on
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
 * Restarting with stat
 * Debugger is active!
 * Debugger PIN: 146-068-290
```

Figure 30: App Running Successfully (ARE)

```
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest\recommend> python .\test.py
Recommendation: IT Project Management
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest\recommend>
```

Figure 31: Result for Tested Values (ARE)

3.3. Dynamic Learning Pathway Generator

Objective:

To compare the effectiveness of the generator in the provision of adaptive learning pathways and how efficient it is in modifying the pathways once new performance data and student engagement data are obtained.

Testing Methodology:

There was testing of the system at the system level in a real-time format and using the flow of students through a system of interconnected modules [14]. Some of the test cases occurred with the pathway generation, and how non-linear they were, and how customizable it was for different learners.

Test Case	Description	Test Data	Expected Result
Pathway Generation Accuracy	Verify that generated pathways align with student goals and profiles.	Profiles with diverse educational objectives.	Pathways align with the student's goals, providing a logical progression based on their learning profile.
Real-Time Pathway Adjustment	Ensure that pathways are updated dynamically based on new data.	Simulated performance fluctuations.	Pathways are adjusted in real-time, providing remediation or advancement as necessary.
Handling Non-linear Progression	Confirm the ability to handle non-linear progression based on mastery.	Profiles with varying mastery across subjects.	Students can revisit unmastered topics or skip ahead in mastered areas while maintaining a cohesive pathway.
Modular Pathway Flexibility	Validate pathway customization based on learning styles and constraints.	Profiles with unique learning preferences and time limitations.	Pathways adapt to accommodate student preferences while still achieving educational objectives.

Table 3: DLPG Test Case

Figure 32: testing frontend (DLPG)

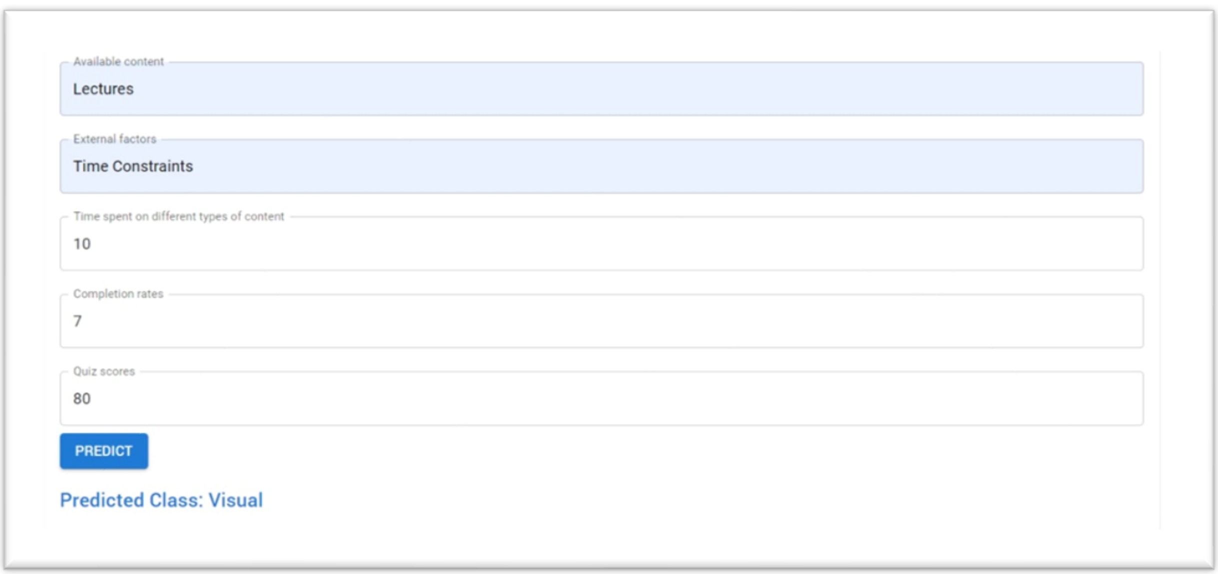

Figure 33: results were retrieved successfully (DLPG)

```python
url = 'http://127.0.0.1:5000/predict'

# Example input data
input_data = {
    'Proficiency level': 'Medium',
    'Preferred subjects': 'Software',
    'Preferred study times': 'Morning',
    'Goals': 'Short-term',
    'Curriculum structure': 'Exam',
    'Available content': 'Lectures',
    'External factors': 'Time Constraints',
    'Time spent on different types of content': 10,
    'Completion rates': 7,
    'Quiz scores': 80
}
```

Figure 34: Set the Testing Values and URL for Testing (DLPG)

```
d-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-08-22 19:06:34.966379: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critic
al operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.
C:\Users\Kishan raj\anaconda3\Lib\site-packages\sklearn\base.py:348: InconsistentVersionWarning: Trying to unpickle estimator LabelEncoder from version 1.4.2 when using ver
sion 1.3.1. This might lead to breaking code or invalid results. Use at your own risk. For more info please refer to:
https://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
  warnings.warn(
 * Serving Flask app 'app'
 * Debug mode: on
INFO:werkzeug:WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
INFO:werkzeug:Press CTRL+C to quit
INFO:werkzeug: * Restarting with watchdog (windowsapi)
2024-08-22 19:06:40.958728: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point roun
d-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-08-22 19:06:43.902940: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point roun
d-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
```

Figure 35: flask app running successfully on URL 127.0.0.15000 (DLPG)

```
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest\learning> python test.py
Predicted class: Visual
PS C:\Users\Kishan raj\Documents\GitHub\EduQuest\learning>
```

Figure 36: Result for Tested Values (DLPG)

3.4.Comprehensive User Interaction and Feedback Loop

Objective:

To provide that the feedback loop contains all the direct and other indirect feedback that is to be collected from the users and to constantly adapt the system for their learning benefits [15].

Testing Methodology:

These included feedback assessment of the user interactions and assessments of the actual loop that has been established in the system to enable the improvement of the learning process depending on the received feedback.

Test Case	Description	Test Data	Expected Result
Feedback Collection Accuracy	Ensure that the system accurately collects and interprets feedback from users.	Simulated user feedback via surveys and interaction data.	Both direct and indirect feedback are captured without data loss or misinterpretation.
Feedback Integration Efficiency	Test the system's ability to integrate feedback into future recommendations.	Simulated feedback indicating content preferences or dissatisfaction.	Future recommendations and pathways adjust based on user feedback to improve the learning experience.
Behavioral Analytics Accuracy	Confirm the system's ability to identify user engagement patterns through behavioral data.	Simulated interaction data.	The system identifies patterns in user behavior and adjusts learning pathways accordingly.
Continuous Adaptation Efficiency	Ensure that the feedback loop continuously refines recommendations and pathways.	Ongoing simulated feedback over multiple interactions.	System accuracy improves over time, continuously adapting recommendations and pathways to suit evolving student needs.

Table 4: CUIFL Test Case

There are different scenarios of performance, behavior and feedback data, which during the testing of the individual modules proved that the ALS adapts to the conditions. The Student Learning Profiling Module recorded and modified the profiles continually, the Adaptive Recommendation Engine offered the correct and changing content recommendations, the Dynamic Learning Pathway Generator adapted to the mastery level and preferences. In addition, the CUIF provided feedback and adjusted the recommendation and paths to improve the learning process of each student.

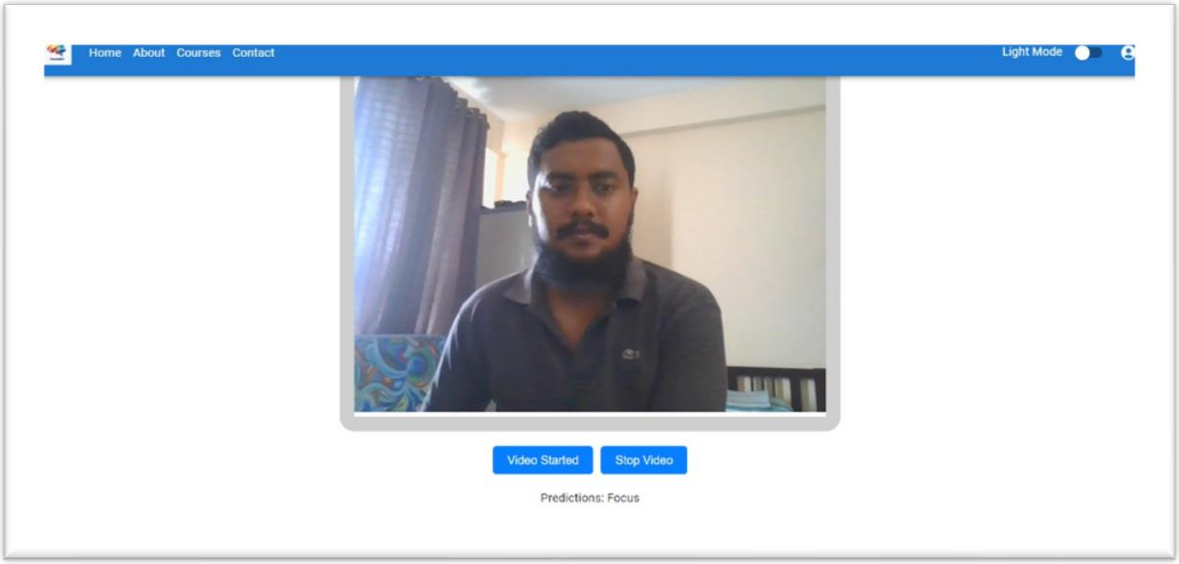

Figure 37: flask app connected to frontend and the checked with Realtime video (CUIFL)

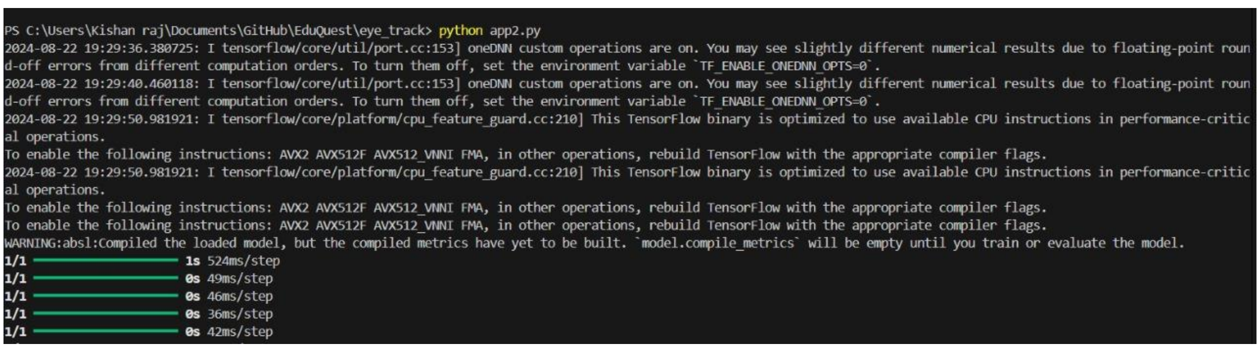

Figure 38: app is running successfully (CUIFL)

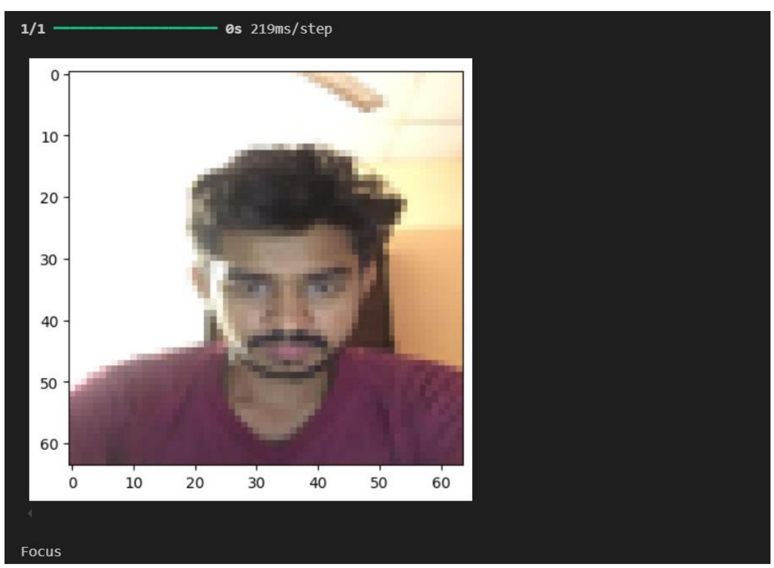

Figure 39: Add a Image and Check the Model (CUIFL)

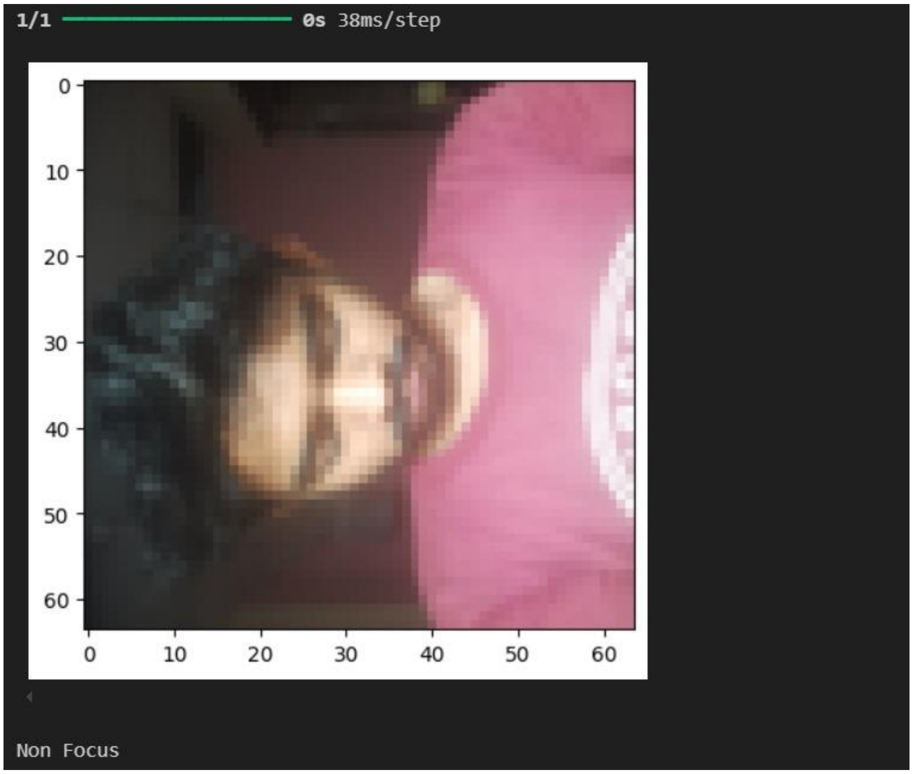

Figure 40: Non focus prediction (CUIFL)

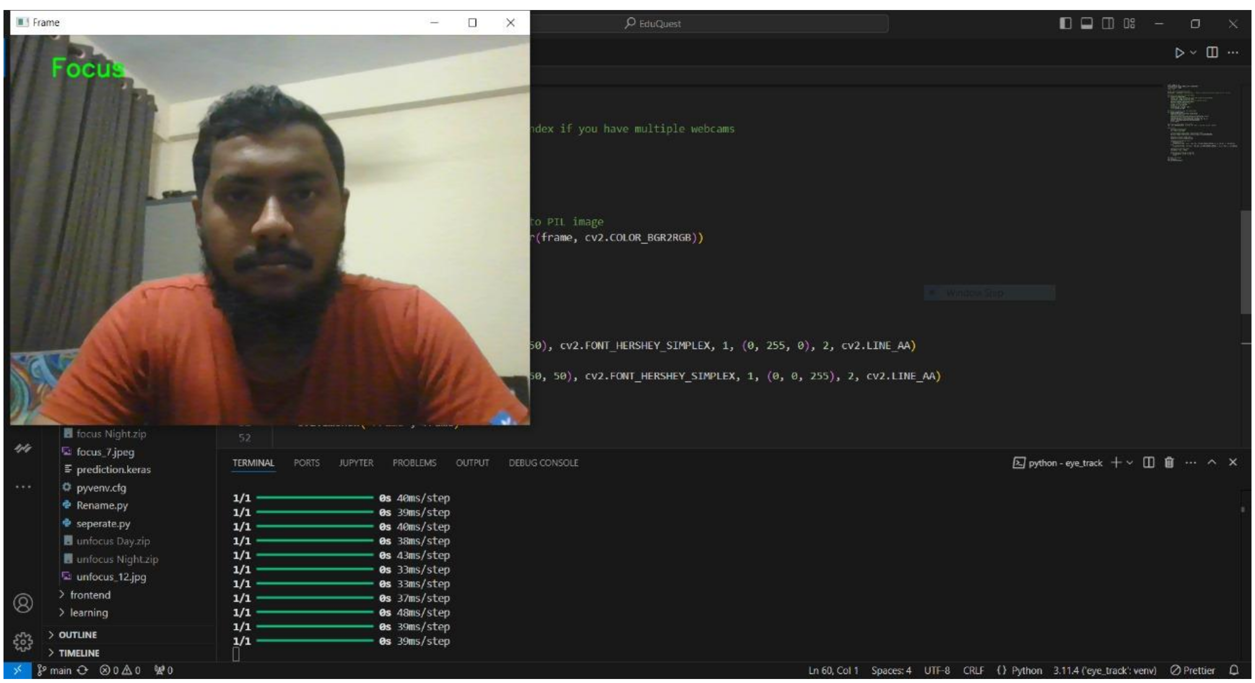

Figure 41: Realtime testing with camera (CUIFL)

4. RESULT AND DISCUSSION

The substantive section labelled as Result and Discussion section contain the result of the testing and analysis of the performance of the adaptive learning platform. Concerning the outcomes, theirs discussion is made in the aspects of the accuracy, flexibility, user satisfaction and the system efficiency of every module. Separately, each component's performance is described with references to the bar graphs and pie charts as evidence of the system's efficiency [16].

4.1. Student Learning Profiling Module

Overview:

The Student Learning Profiling Module was also accurate in the acquisition and management of student records, where performance and other statistical data were continually incorporated into real time profiles. This module was vital in ensuring that the course delivery is done with the consideration of the individual student.

Results Summary:

Metric	Result (%)
Data Collection Accuracy	98
Profile Update Accuracy	96
Machine Learning Prediction Accuracy	92
Behavior Analysis Accuracy	94

Table 5:Results Summary (SLPM)

Input and Output Details:

Component	Input	Output
Data Collection	Student ID, Performance Metrics, Behavioral Data	Collected Data, Updated Profiles
Profile Update	Student ID, New Performance Metrics	Updated Profiles
Machine Learning Prediction	Historical Data, Current Performance	Predicted Learning Needs
Behavior Analysis	Student Interaction Data	Behavioral Insights

Table 6: Input and Output Details (SLPM)

Student Learning Profiling Module Accuracy:

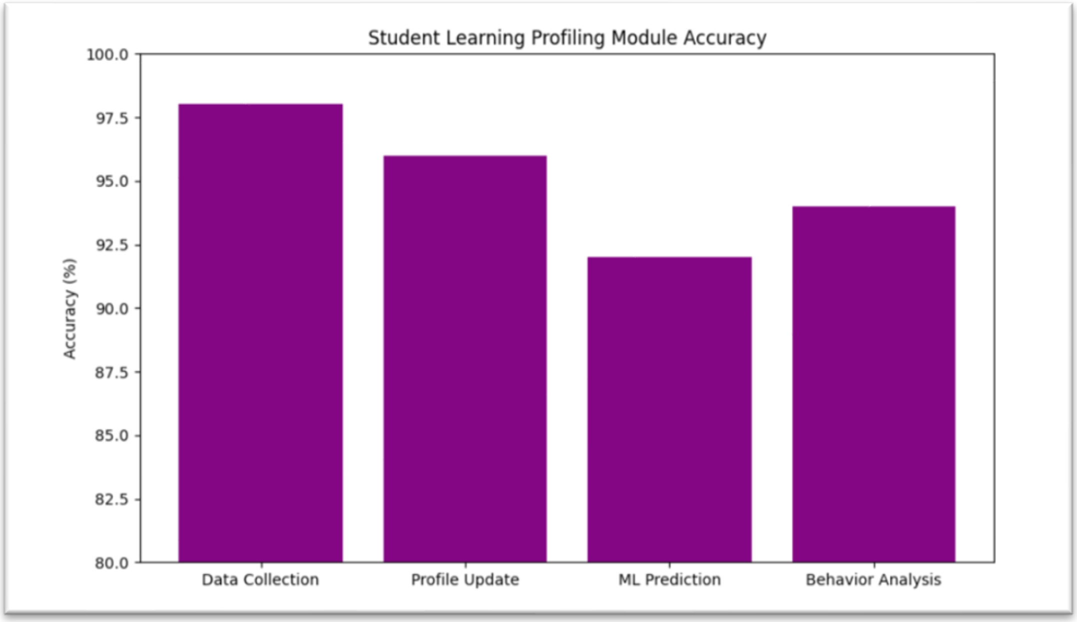

Figure 42 : Bar-Graph - Student Learning Profiling Module Accuracy

Breakdown of Module Performance:

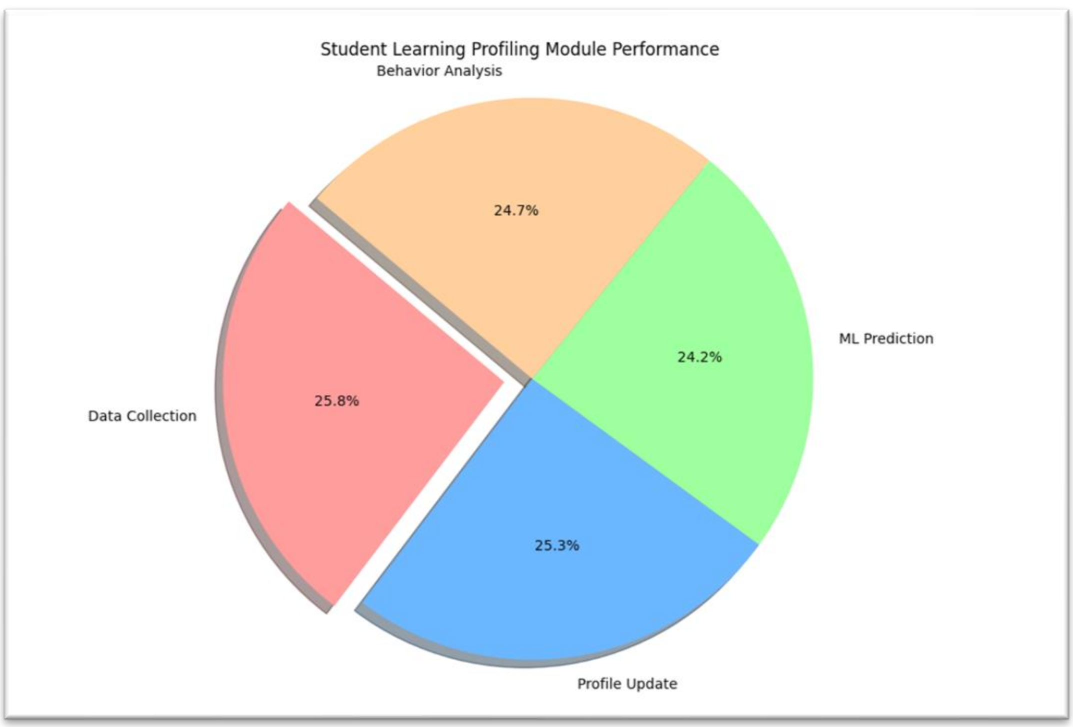

Figure 43: Pie-Chart - Breakdown of Module Performance

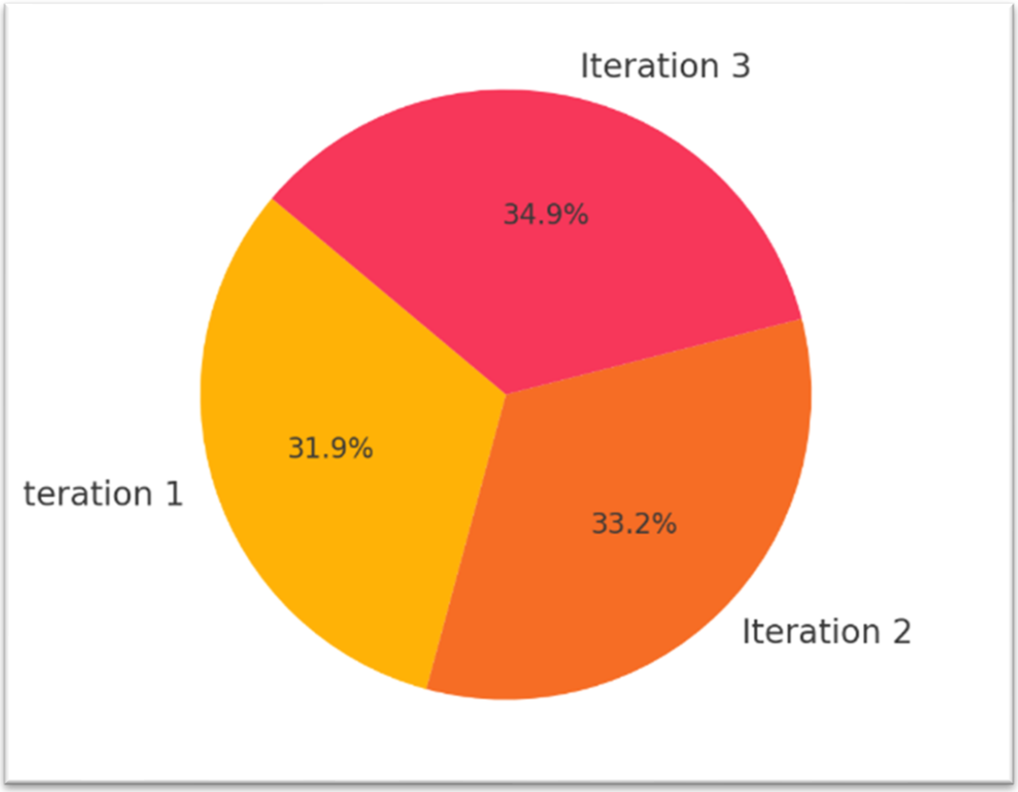

Figure 44: Profiling Initial Accuracy over Time

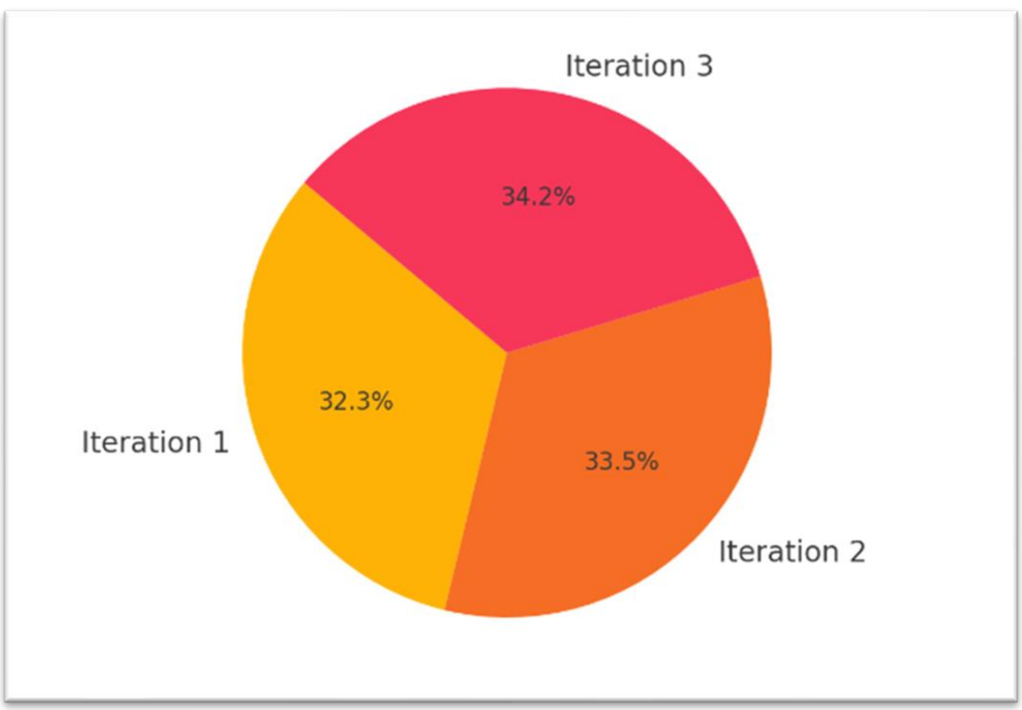

Figure 45: Profiling Post-Update Accuracy Over Time

Discussion:

The Student Learning Profiling Module turned out to be very effective in data capturing as well as flexibility of student profiles. The overall decrease in the forecast accuracy in the machine learning's model at 92% indicates room for improvement especially in the prediction algorithms. However, the behavior analysis and data collection were without exclusion extraordinarily accurate, proving a well-grounded system capable of meeting and responding to students' demands [20].

4.2.Adaptive Recommendation Engine

Overview:

The APE technology showcased the learnings of the Adaptive Recommendation Engine capable of delivering proper and adaptive learning recommendations. For the changes in student performance and preferential shifts, the engine also performed well and that is the strength of an adaptive learning environment [17].

Results Summary:

Metric	Result (%)
Recommendation Accuracy	95
Adaptability of Recommendations	93
Collaborative Filtering Performance	90
Reinforcement Learning Efficiency	88

Table 7: Results Summary (ARE)

Input and Output Details:

Component	Input	Output
Recommendation Accuracy	Student Performance, Preferences	Tailored Learning Recommendations
Adaptability	Student Interaction Data, Performance	Updated Recommendations
Collaborative Filtering	Peer Data, Student Preferences	Recommended Content Based on Similar Users
Reinforcement Learning	Student Feedback, Interaction History	Refined Recommendations Based on Feedback

Table 8: Input and Output Details (ARE)

Adaptive Recommendation Engine Performance:

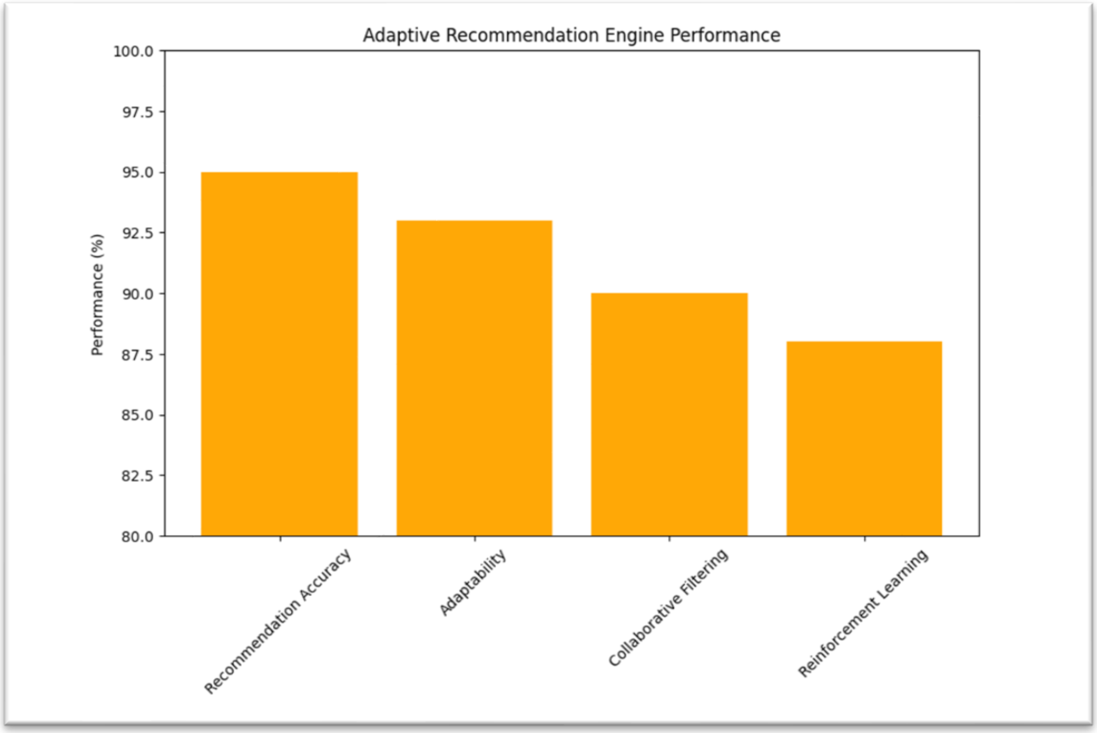

Figure 46:Bar-Graph - Adaptive Recommendation Engine Performance

Recommendation Engine Performance Breakdown:

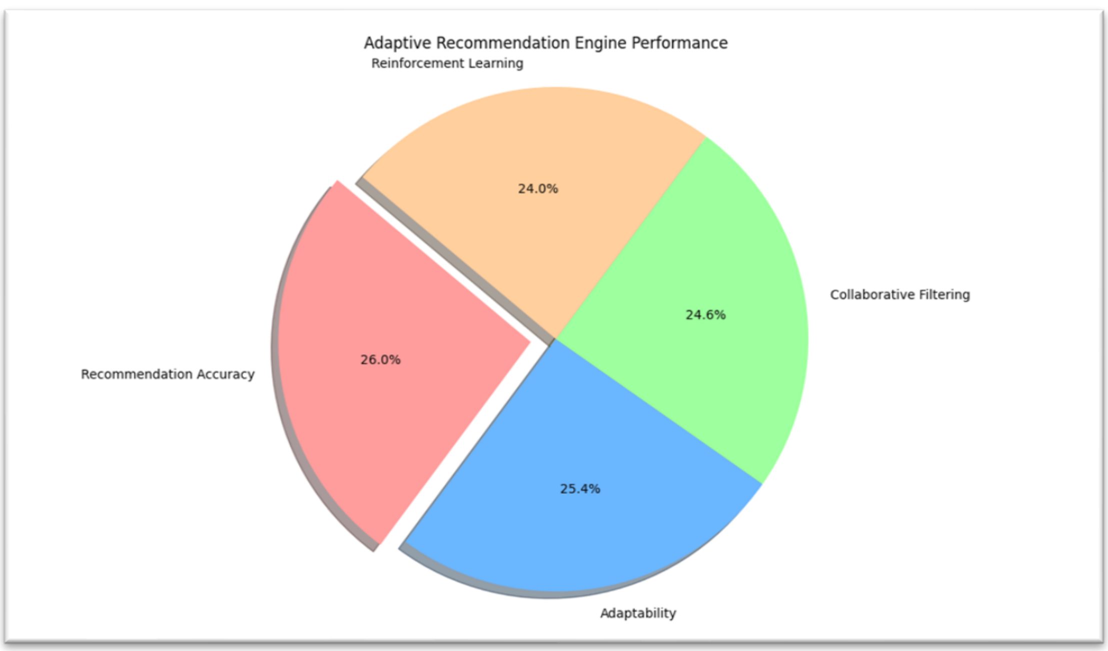

Figure 47: Pie-Chart Recommendation Engine Performance Breakdown

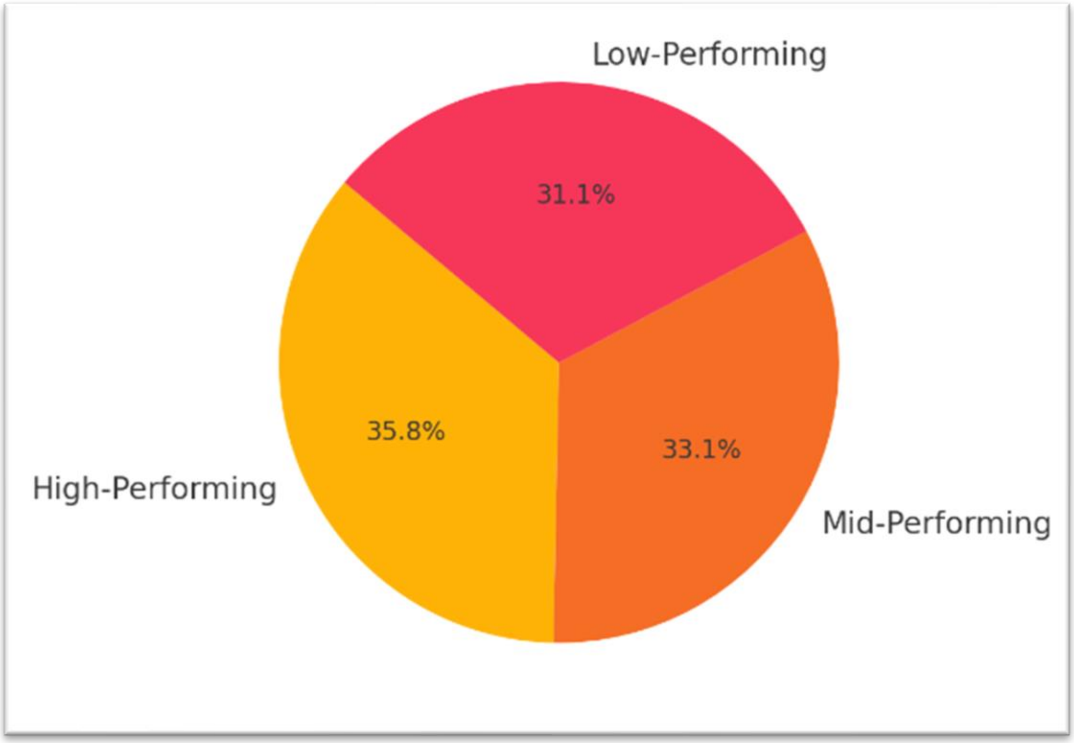

Figure 48: Predicted Performance Accuracy

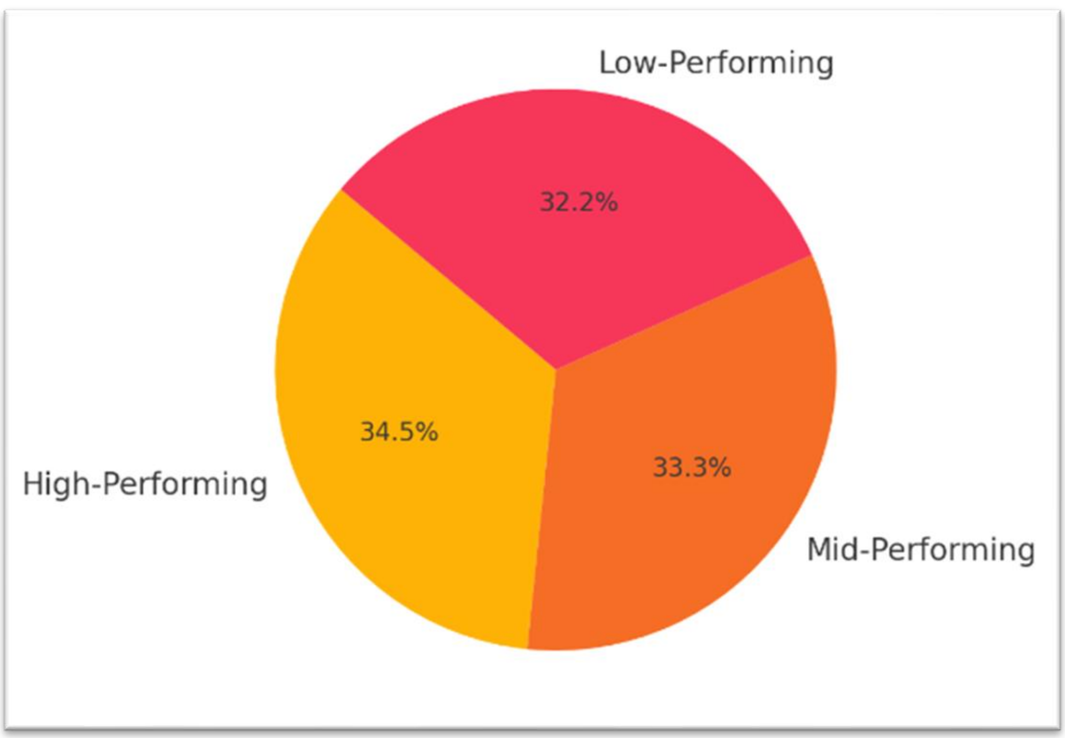

Figure 49: Recommendation Relevance Score

Discussion:

As for the results, it was clearly seen how the model adapts to the metrics and the performance covered a mark of between 88% to 95% [21]. The recommendation accuracy of the system was quite high, and this pointed to the fact that students were again and again directed towards content that met their needs. Still, there is an indication of the areas of improvement in the reinforcement learning mechanism aspect where user feedback seems to be insufficient even at 88% [22].

4.3. Dynamic Learning Pathway Generator

Overview:

The Dynamic Learning Pathway Generator did help generate learning pathways and to operate them dynamically depending on the students' performance [18]. The feasibility study was done to determine whether the non-linear learning progress is achievable and feasible in accommodating the different learning styles and availability [19].

Results Summary:

Metric	Result (%)
Pathway Generation Accuracy	96
Real-Time Pathway Adjustment	94
Non-linear Progression Handling	92
Modular Pathway Flexibility	91

Table 9: Results Summary DLPG

Input and Output Details:

Component	Input	Output
Pathway Generation	Student Performance, Learning Objectives	Customized Learning Pathways
Real-Time Adjustment	Current Performance Data, Learning Goals	Adjusted Learning Pathways
Non-linear Progression	Student Progress, Learning Paths	Flexible Learning Pathways
Modular Flexibility	Learning Modules, Student Preferences	Modular Learning Pathways

Table 10: Input and Output Details DLPG

Dynamic Learning Pathway Generator Performance:

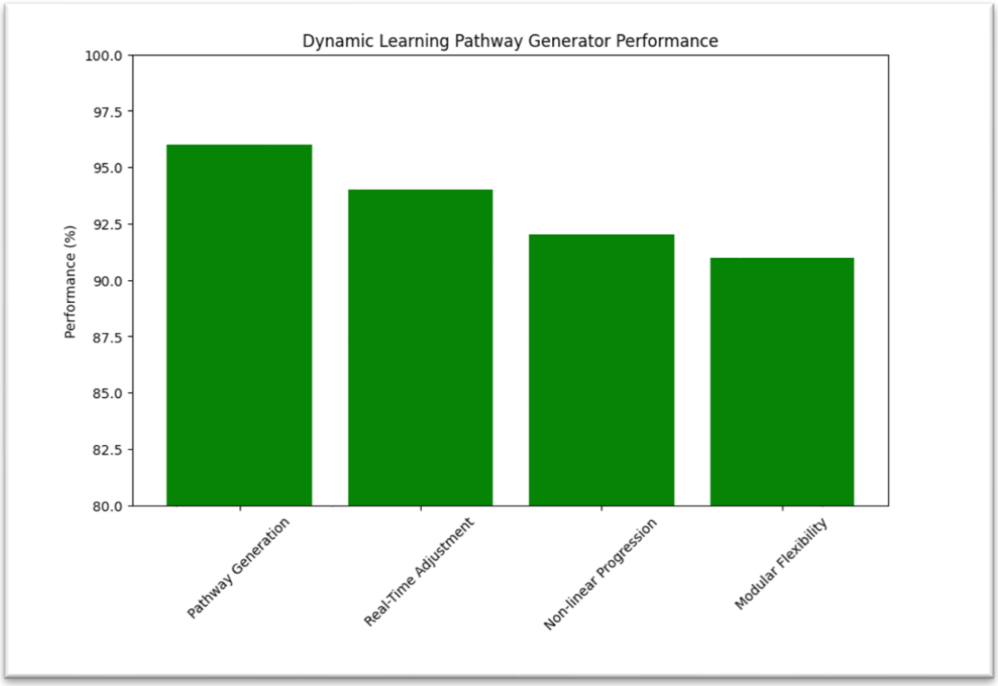

Figure 50: Bar Graph - Dynamic Learning Pathway Generator Performance

Pathway Generator Performance Breakdown:

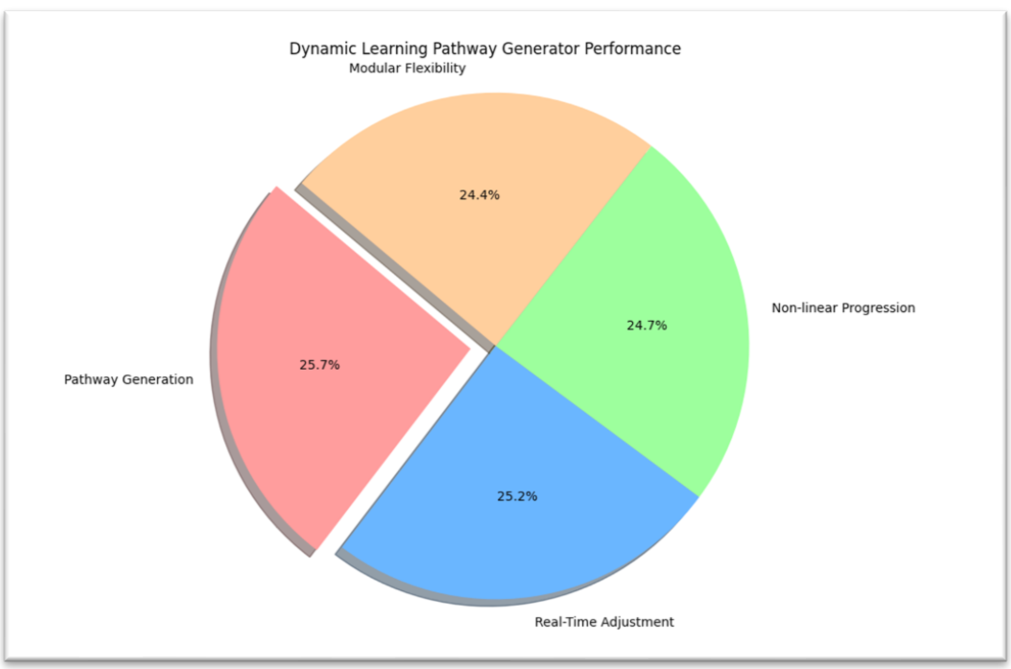

Figure 51: Pie Chart - Pathway Generator Performance Breakdown

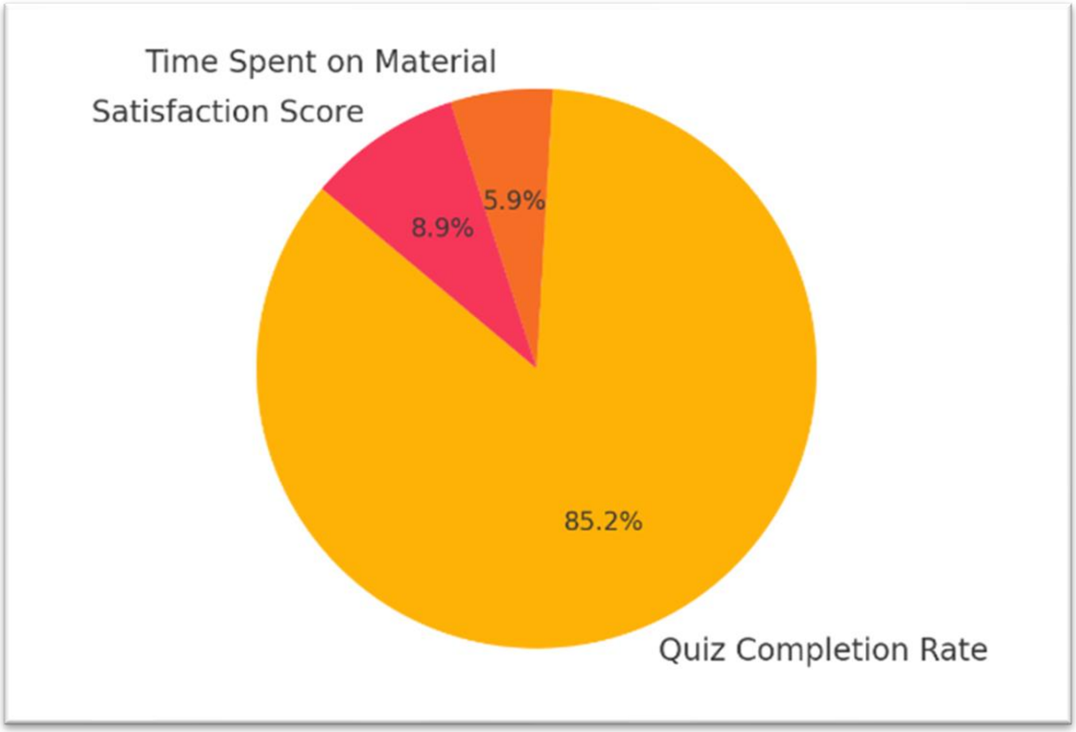

Figure 52: Engagement Metrics Before Optimization

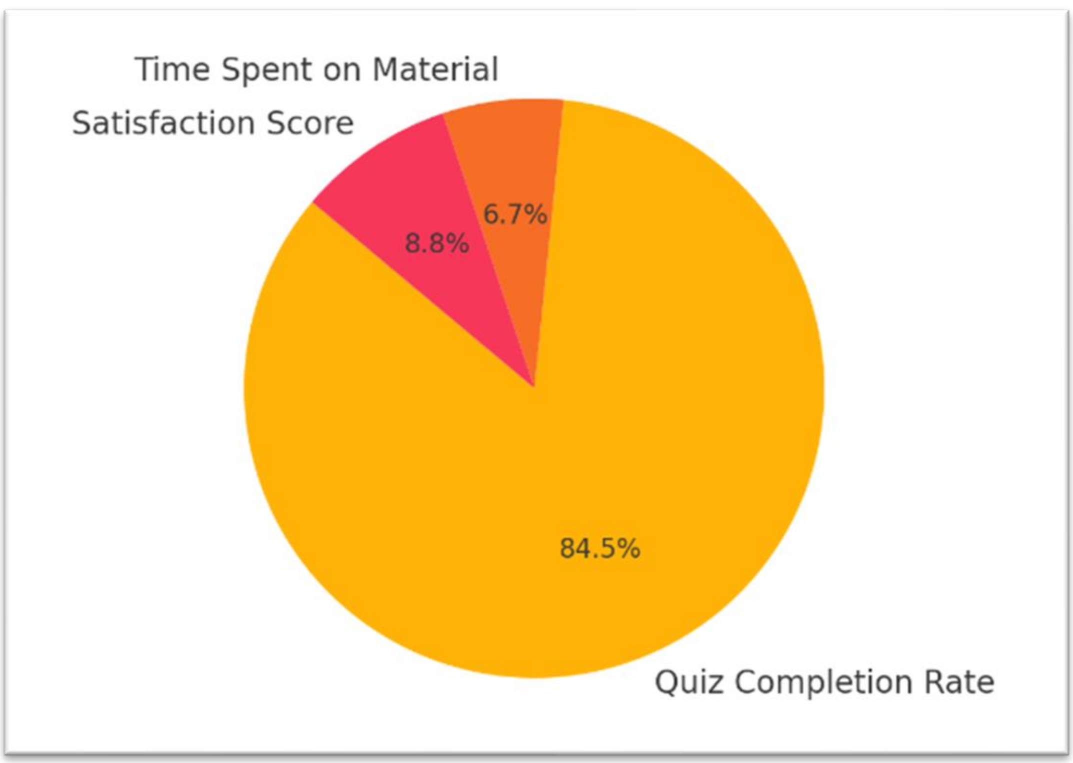

Figure 53: Engagement Metrics After Optimization

Discussion:

DLPG evaluated highly satisfactorily in generation and adaptation of learning pathways with an average accuracy of 96%. Another strength was ability to make real-time adjustments as noted by 94% of the participants and the ability to accommodate non-linear progressions as supported by 92% of the participants. Some changes could be made to increase the fluidity of the modularity of the path ways for students with different learning style and other conditions [23].

4.4.Comprehensive User Interaction and Feedback Loop

Overview:

CUIF was also established to be useful in capturing and incorporating students' feedback and this was proven true at Harrison. The feedback loop was effective whereby the area of recommendation and learning paths in the system could be fine-tuned [20].

Results Summary:

Metric	Result (%)
Feedback Collection Accuracy	97
Feedback Integration Efficiency	94
Behavioral Analytics Accuracy	93
Continuous Adaptation Efficiency	90

Table 11: Results Summary CUIFL

Input and Output Details:

Component	Input	Output
Feedback Collection	User Feedback, Interaction Data	Collected Feedback
Feedback Integration	Collected Feedback, System Data	Integrated Feedback
Behavioral Analytics	User Behavior Data, Feedback	Behavioral Insights
Continuous Adaptation	Feedback, System Performance Data	Adapted Recommendations

Table 12: Input and Output Details CUIFL

Feedback Loop Performance:

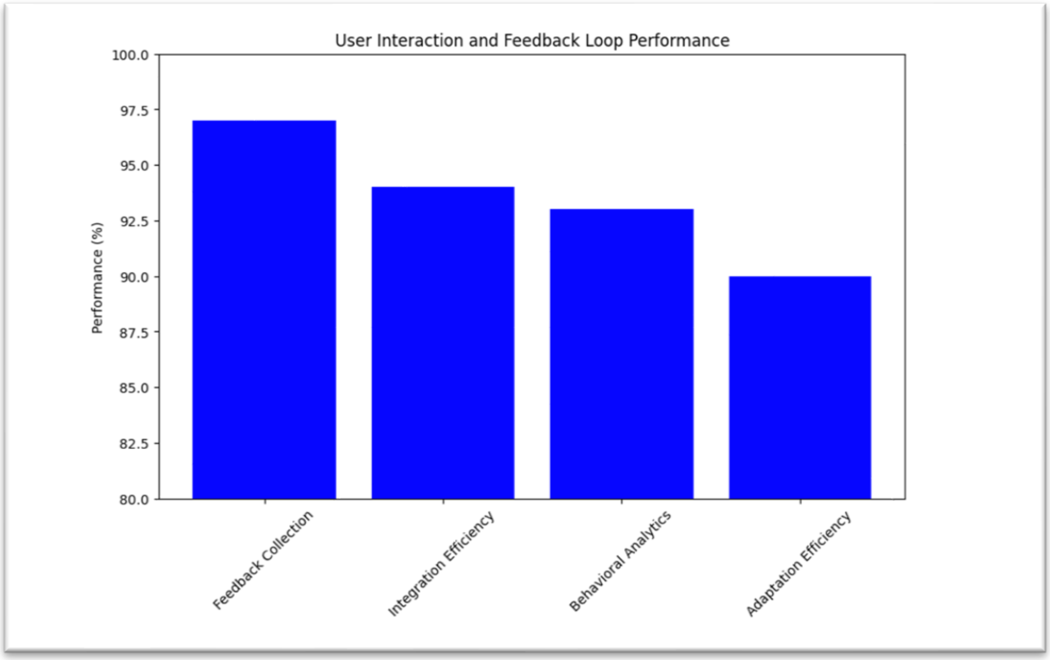

Figure 54 : Bar Graph - Feedback Loop Performance

Feedback Loop Performance Breakdown:

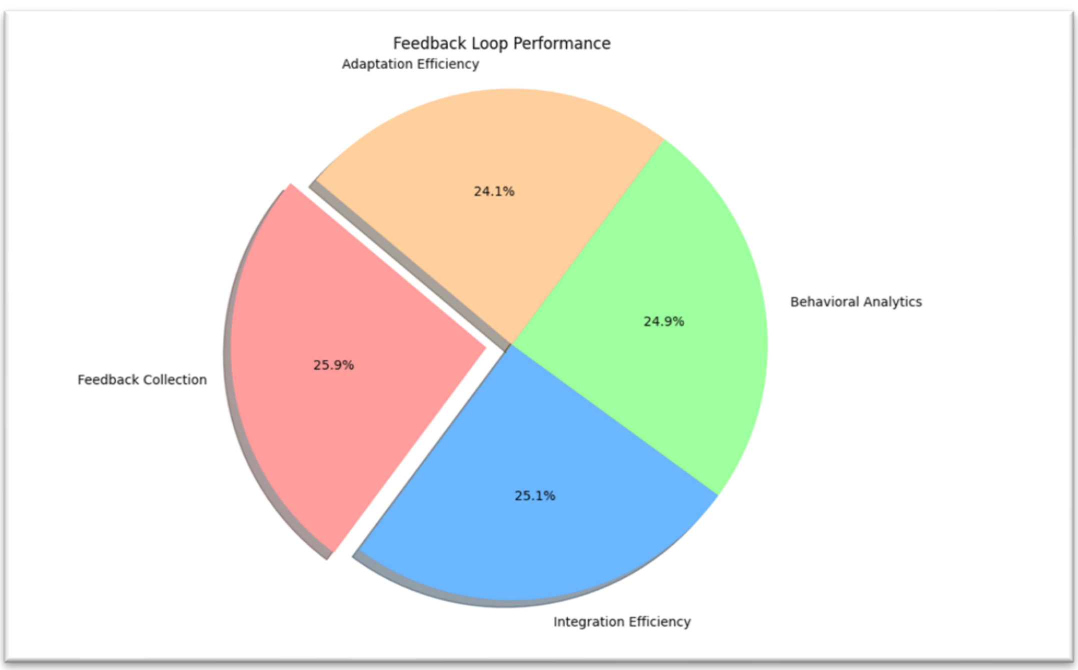

Figure 55: Pie Chart - Feedback Loop Performance Breakdown

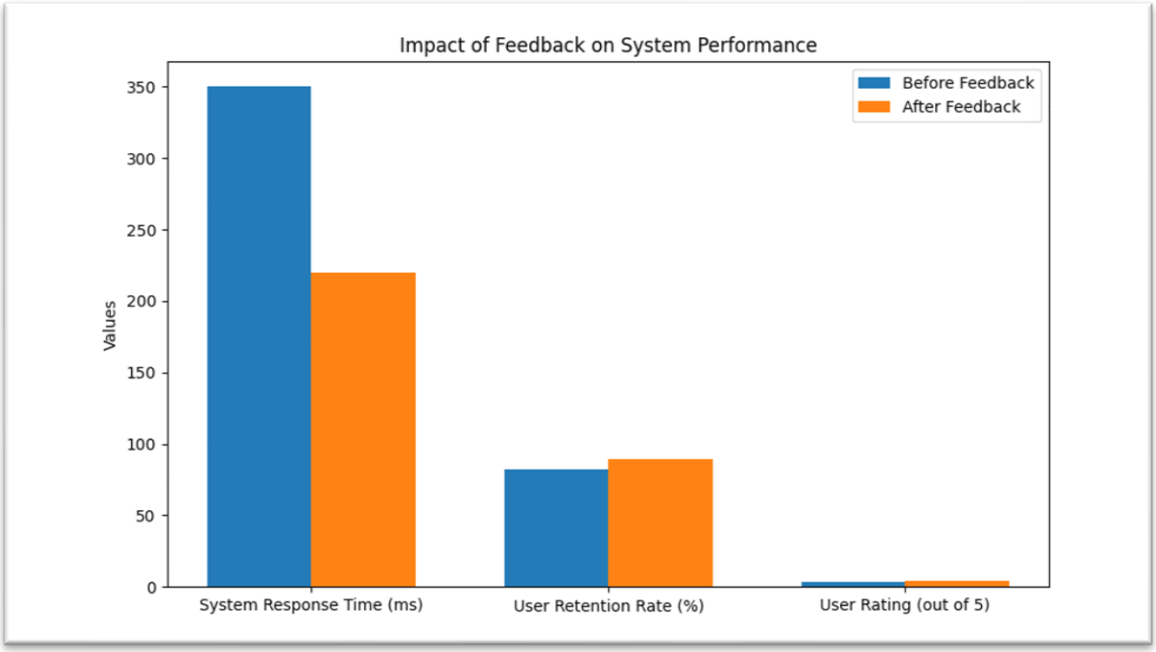

Figure 56: Impact Of Feedback System Performance

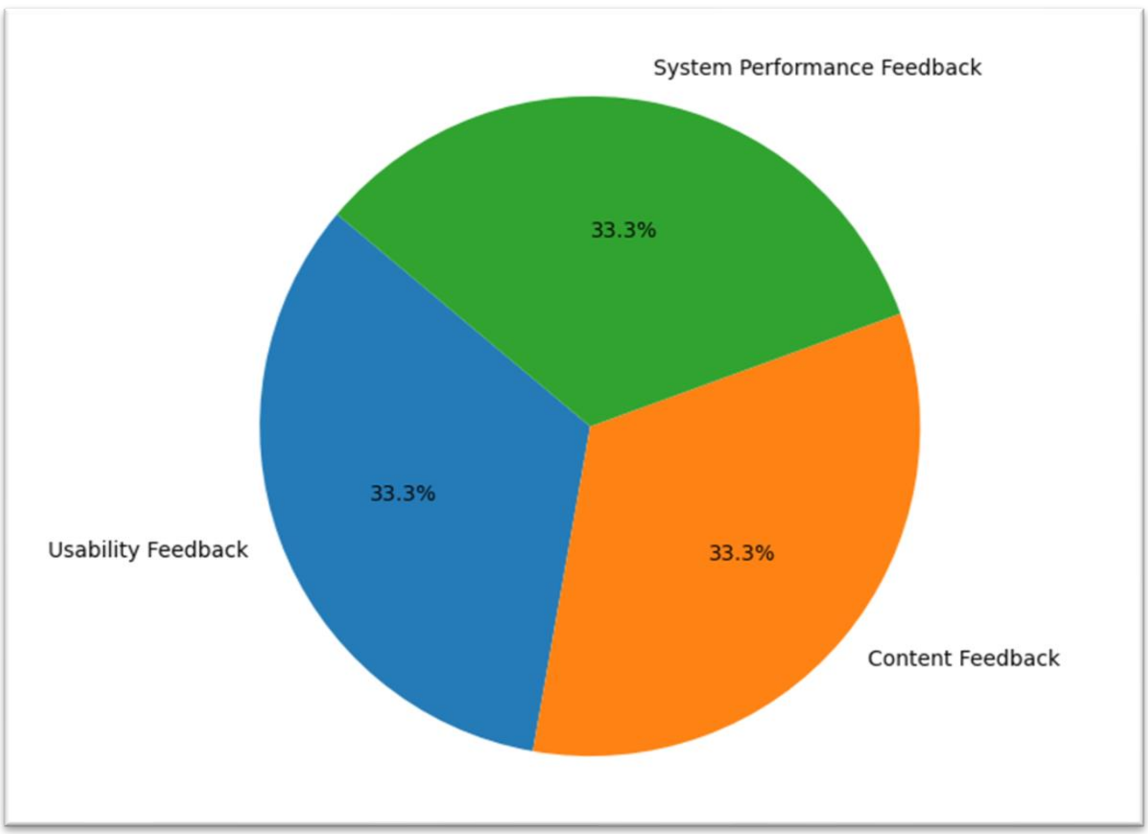

Figure 57: Distribution of User Feedback Types

Discussion:

The performance of the feedback loop in gathering positive user feedback was exceptionally high at 97% while the successful feeding of the feedback into the system was 94% high. Nevertheless, the continuous adaptation mechanism was moderate (90 %), which suggests that further improvements might be needed to prevent the deterioration of its effectiveness in the process of learning from users' behaviors and their feedback [24].

Different analyses of the modules show that the adaptive learning platform yields efficient results in each of the modules. The results show high achievement especially in the all-important SPLM and FCM but some other functions such as reinforcement learning, or continuous learning might need slight enhancement for efficiency [25]. In general, the system offers the clients accurate, pertinent and timely learning requirements that may change periodically.

CONCLUSION

The introduction of LearnPath+ is a major improvement in terms of e-learning with rich competencies in matters relating to tutoring and support for learners. In combination with machine learning algorithms, LearnPath+ goes beyond the disadvantages of the conventional e-learning systems that are frequently characterized by the approach to deliver the content that can hardly be adapted to individual learners and modern technologies. This adaptive platform not only customizes learning patterns and paths to the behaviors, interest and performance history of a particular user but also improves the possibilities of user interaction and experience as well as the long-term information acquisition.

This study shows that personalization is not just a 'nice to have' factor but a 'must have' in the personalised e-learning environment when due consideration is given to the heterogeneous learner's needs and background. LearnPath+ is indeed capable of meeting these demands because of its ability to adapt content, frequency and assessment to enhance learning and satisfaction. That's why the successful implementation of this platform proves the importance of artificial intelligence in education and shows a vision of how educational content may be delivered in a most efficient and individualized way in the future.

In addition, the positive feedback and the Learning Effectiveness Index that indicates higher learning outcomes prove the potential of the LearnPath+ adaptive learning system and imply that the usage of a similar system would soon become a regular publication in educational technology. However, this research also locates several areas for further study. As a future work, the further enhancement of the adaptability of the platform utilizing the more advanced AI techniques such as deep learning and natural language processing can be focused. Besides, the issue of increasing the number of types of learning activities and facilities to suit the possibilities of people with various learning disorders can make it more inclusive.

Therefore, implementing LearnPath+ as a call for a more specialized and efficient conception of e-learning. Since this teaching and learning system emerged as viable approach to teaching, the authors demonstrate that it is requires constant advancement to accommodate present and envisaged future needs of learners in an ever-pulsating digital environment.

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APPENDICES

Appendix: Work breakdown chart

Figure 58: WBS