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**Personalising Learning Through Emotions to Improve Educational  
Experience: Sentellect**

In partial fulfilment of the requirements for the degree of  
**Bachelor of Science in Information Technology**

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## Certificate



We accept the work contained in the report titled  
“Personalising Learning Through Emotions to Improve Educational  
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## DECLARATION

We hereby declare that this project report is based on our original work except for citations and quotations which have been duly acknowledged. We also declare that it has not been previously and concurrently submitted for any other degree or award at Bahria University or other institutions.

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Specially dedicated to my  
beloved mother and father

(Malaika Saleem)

my beloved grandfather, mother and  
father

(Zara Asif)

my beloved mother and father

(Saud Ahmed)

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## **Personalising Learning Through Emotions to Improve Educational Experience: Sentellect**

### **ABSTRACT**

This document introduces Sentellect, a web-based adaptive learning system powered by AI, aimed at improving educational experiences for 12th-grade Mathematics (PTB) students through the incorporation of emotional state analysis into content delivery. The primary aim is to go beyond conventional performance metrics by evaluating a student's cognitive and learning abilities through an extensive survey assessment. A Random Forest classifier, trained and validated with an accuracy of 96.60%, is employed to forecast student distress levels (Low, Moderate, High) using these inputs. This forecast, combined with performance metrics, powers the personalization engine, creating a customized learning pathway. To foster trust and acceptance, the system includes an Explainable AI (XAI) element to deliver transparency for every learning suggestion. Additionally, a unified Chatbot driven by a Large Language Model (LLM API) provides immediate assistance and emotional backing. The completed Sentellect web application, created with Python Flask and HTML/CSS, showcases a thorough solution that adjusts content complexity, speed, and assistance methods in real-time, promoting a more supportive, interactive, and efficient educational setting.

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**LIST OF SYMBOLS / ABBREVIATIONS**

<i>RF</i>	Random Forest
<i>LLM</i>	Large Language Model
<i>XAI</i>	Explainable Artificial Intelligence
<i>API</i>	Application Programming Interface
<i>PTB</i>	Punjab Textbook Board
<i>D</i>	Dataset

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## CHAPTER 1

### INTRODUCTION

#### 1.1 Background

In Today's world mental health has become a major concern of society especially with increasing academic pressure and responsibilities on peers. Mental stress is one of the most common and unnoticed conditions affecting students and this exposure to continuous stress results in emotional exhaustion which can result in reduced productivity, low motivation and weak decision making. To address these mental issues Personalization has come into existence as a powerful approach. The term Personalization refers to delivering learning content, explanations, concepts, and feedback that matches the need of every individual learner's state unlike one-fits-all approach where individuals are bound to follow the same learning style. With advances in AI and Large Language Models (LLMs) personalization has become more practical. Personalization helps to analyse student responses, detect the gaps in learning and understand the student's stress level and generates questions and explanation automatically. In mathematics personalization makes the concepts more understandable for the students and helps strengthen their critical thinking skills with guidance feels like one-on-one tutor.

#### 1.2 Research Gaps:

Several studies have explored AI-based personalization, but most of them focus on adaptive quizzes and recommender systems. These systems often depend upon predefined logic and limited datasets, and they are generally good at analysing what we do, our clicks, our quiz scores, our references. However, a significant limitation persists in emotions, and they remain ignored the systems do not see why we do certain actions and the reasoning behind them. For that the dynamic assessment of learner affective state is necessary [1]. The confused, frustrated, and curious state of mind can

affect the ability of person to pay attention and stay motivated to certain tasks [2]. As the Lithuanian case study hinted, students with strong learning preferences face more challenges in traditional settings, and these challenges are often deeply emotional [3]. Very few studies have integrated the AI to personalize the mathematics content specifically for their local curriculum. Moreover, previous studies lack the touch of empathy and cognitive ability to explain the content according to each individual level. These types of platforms track your performance not your experience. This highlights the need for intelligent systems like Sentellect where emotion meets experience[4].

### **1.3 Aims and Objectives**

Sentellect was developed in response to this growing need. A Personalized AI-powered solution designed to analyse behavioural patterns for 12<sup>th</sup> Grade Mathematics (PTB – Punjab Textbook Board) using AI model. The goal of Sentellect is to analyse the student's input, identify misconceptions and keep students motivated by understanding how they feel (here term how refers to broader aspect by identifying student's stress, frustration or motivation level), removing distractions (by using attention-tracking technology sends gentle messages or reminders to student by appreciating them on each section) and providing personalised encouragement (by rewards, animations and game challenges). Unlike previous tools, personalization has not been performed before using this specific AI-based approach for PTB Class 12<sup>th</sup> Mathematics, making this research unique and impactful for local educational needs. The goal is to create a study partner that keeps peers motivated, productive and emotionally balanced.

### **1.4 Contribution:**

This research introduces one of the first AI-powered emotion detection personalized learning systems specifically tailored to the PTB 12th-grade mathematics curriculum. A trained Random Forest model is incorporated to predict the stress level of the students based on their responses, behaviour, and self-reported indicators. The Random Forest model has achieved accuracy of 96%, indicating its reliability in identifying students who are experiencing higher stress. The model is developed using features inspired by the DASS (Depression, Anxiety, and Stress Scale) dataset, allowing it to identify signals of anxiety, confusion, and cognitive overload during learning activities. We explore its potential to make learning not just more personalized, but more

supportive and human. We also address the real-world challenges of such a system, including data privacy and the need for teacher collaboration and something rule-based systems cannot achieve. By bridging the gap between cognitive performance and emotional state, Sentellect aims to create a future where education is not only intelligent but also instinctively understanding.

This research introduces one of the first AI-powered personalized learning systems specifically tailored to the PTB 12th-grade mathematics curriculum. A trained Random Forest model is incorporated to predict the stress level of the students based on their responses, behavior, and self-reported indicators. The Random Forest model has achieved accuracy of 96%, indicating its reliability in identifying students who are experiencing higher stress. The model is developed using features inspired by the **DASS (Depression, Anxiety, and Stress Scale) dataset**, allowing it to identify signals of anxiety, confusion, and cognitive overload during learning activities. We explore its potential to make learning not just more personalized, but more supportive and human. The system also incorporates a chatbot for real-time assistance to students enabling them to receive guidance instantly whenever they feel any difficulty with concepts. Additionally, Sentellect intelligently analyzes the student's behavior. If the student is repeatedly scrolling or spending too much time on practice questions or showing signs of difficulty, it can proactively suggest a more suitable content level to improve comprehension and reduce cognitive load.

By bridging the gap between cognitive performance and emotional state, Sentellect aims to create a future where education is not only intelligent but also instinctively understanding.

## CHAPTER 2

### LITERATURE REVIEW

#### 2.1 Personalized & Emotion-Aware Learning

Personalized learning systems have emerged as a revolutionary influence in contemporary education, providing customized instructional experiences that adjust to each student's cognitive abilities, speed, interests, and emotional condition. In contrast to conventional uniform teaching approaches, personalized systems utilize data informed insights and artificial intelligence to guarantee that each learner obtains content tailored to their individual strengths and weaknesses. This personalized strategy leads to increased participation, less cognitive strain, better knowledge retention, and heightened motivation. Personalized learning systems foster a more inclusive, effective, and empowering educational atmosphere for students of all abilities and backgrounds by modifying learning paths, difficulty levels, feedback processes, and even providing emotional support in real-time.

The purpose of this study is to reshape the way knowledge is delivered, understood, and retained. Our studies show that emotional processing parameters can be measured and integrated into web-based learning environments to personalize content and improve learning performance. In today's era, the integration of Artificial Intelligence has rapidly emerged in transforming the traditional system into a personalized system. It shatters the myth of one-size-fits-all education by empowering learning with a real-time emotional compass. The contribution of AI in developing personalized learning through sophisticated emotion recognition transforms digital education into a more empathetic, responsive, and human-centered experience. It bridges the gap between emotional awareness and cognitive learning, helping students overcome anxiety, improve concentration, and build confidence. The intersection of AI and emotional intelligence helps to fill the gaps lying in students' learning due to emotional variations. Learning is a combination of not only cognitive processes but also emotional experience.

#### 2.2 Core Foundations of Personalized Learning

The review of article [5] on Personalized learning is a way of teaching where each student gets lesson that just fits for them. Instead of everyone doing the same thing at the same time, the lesson customized on each student needs, what they absorb at a time, and how they learn best. Not just the traditional system where all students do the exact work no matter what.

### **2.3 Personalized E-Learning Content and Emotional Adaptation**

The main design concept of [6] focuses on personalization through an Adaptive E-Learning Environment (ALE). The engagement activity focuses on personalizing education by automatically modifying the learning material, delivery techniques, resources, and even session duration according to each student's unique learning style and existing knowledge level. This customized method serves as the means to greatly enhance student involvement.

The paper [7] discusses student engagement through personalized recommendations implemented using a modular rule-based system in online learning. The core activity for engagement is the adaptive sequencing of learning tasks, which works to keep students focused by maintaining optimal difficulty ensuring tasks are neither too easy nor too difficult for their current level. This system continually adjusts recommendations to align with key pedagogical principles (like spaced repetition and mastery learning), thereby preventing frustration and cognitive overload, which are major causes of disengagement.

This paper [8] states that to assist students who might be emotionally damaged (by generating positive emotions), educational resources should incorporate emotional design (such as inviting colors and approachable visuals). Importantly, this favorable emotional design greatly improves learning results solely when combined with tasks of moderate difficulty. The design effect vanishes in low or high-difficulty situations, indicating that content needs to be crafted to be suitably challenging to enhance the motivational advantage for the learner.

The content for e-learning settings should be crafted to intentionally evoke and regulate particular Learning-Centered Affective States (LCASs) [9]. For students facing emotional challenges, this means purposefully creating content that evokes both positive emotions (such as curiosity and engagement) and, in a managed manner,

negative emotions (such as confusion or frustration). The primary objective is to allow the technology to recognize a negative emotional state and promptly provide a suitable adaptive response (like suggestions or easier material) before the situation intensifies into complete distress.

The article [10], outlines content tailored to the student's anxiety level by introducing a model for an Affective Tutoring System (ATS). This system is intended to identify and categorize the student's anxiety level throughout the learning experience. Once a certain stress level is detected, the ATS subsequently modifies the multimedia learning material instantly. This adjustment might include changing the format of the presentation, tweaking the task's complexity, or altering the resources provided. The primary aim is to utilize this content specification to reduce the adverse effects of anxiety and guarantee that the learning environment consistently caters to the student's current emotional and cognitive requirements, thus enhancing learning results

This paper [11] suggests creating e-learning content, particularly for stressed students, by implementing the Universal Design for Learning (UDL) framework in the Moodle platform. This method emphasizes adaptability and inclusivity to successfully lessen anxiety and eliminate learning obstacles. Important practical design uses involve employing conditional activities in Moodle that allow students to access new resources and assignments solely after they've completed necessary prerequisites, thereby reducing information overload. Additionally, the framework promotes the use of adaptable assessment techniques such as flexible quiz attempts and deadlines to directly reduce academic pressure, which is a major contributor to student stress, as well as the availability of multimodal content (text, video, audio) to address various learning styles and enhance understanding.

#### **2..4 AI's Role in Personalized Learning & Educational Technology**

The review [12] is focused to examine the diverse role of AI in education, particularly concentrating on how it facilitates personalized learning and changes educational technology. The authors explore the various efforts in AI-based applications such as personalized content delivery and smart tutoring systems, assessing their influence on student achievement and involvement. They determine that although AI has great potential to foster inclusive, efficient, and personalized learning spaces that reduce

educational disparities, its successful and fair integration requires joint initiatives to develop ethical standards and tackle issues such as privacy and algorithmic bias.

This systematic literature review [13] aimed to uncover the existing trends and uses of technologies and Artificial Intelligence (AI) in education, focusing particularly on Personalized Learning (PL). The project entailed an extensive review of existing literature to outline the changing functions of different technologies and AI methods (including Machine Learning) in developing personalized, adaptable educational settings. The authors determined that the findings strongly indicate a growing focus on AI and advanced analytics to enhance effective personalization; however, they emphasize the necessity for upcoming studies to concentrate on long-term ethical implications and substantial evaluation frameworks to guarantee sustainable and meaningful implementation.

## **2.5 Smart, Adaptive & Intelligent E-Learning Systems**

The primary focus of the conversation is the transformation of conventional e-learning platforms into smart e-learning systems through the use of Big Data and modern information technologies. Customized systems are essential since as the number of users and the amount of data increases, the "universal" approach does not address personal requirements. Tailored systems utilize AI to analyze this data, adjust course delivery, and enhance a more adaptable and efficient learning experience for every learner according to the article [14].

The author [15] provides a systematic review AI-based personalized e-learning systems, focusing on identifying their key issues, technical challenges, and potential solutions. The study culminates in proposing an integrated architectural framework that leverages multiple AI techniques to address current fragmentation. As AI contributes to personalized learning by enabling systems to be adaptive and responsive to each student's profile. It uses techniques like Educational Data Mining to assess the learner's comprehension level, goals, and preferred learning style. Based on this holistic model, AI algorithms (such as Recommender Systems) then automatically adjust the curriculum, recommending specific content, assessments, and learning paths tailored precisely to the student's needs for optimal effectiveness.

The primary focus of this systematic review [16] is the incorporation of Artificial Intelligence (AI) and Machine Learning (ML) algorithms into flexible e-learning systems. The research finds that AI plays a crucial role in tailoring educational experiences, effectively resulting in optimized learning trajectories, increased student involvement, and better academic outcomes in e-learning systems.

This systematic mapping study [17] aimed to assess the advancement of AI-driven adaptive learning systems by examining existing literature to recognize and classify ongoing research. The conversation focused on illustrating the various AI interventions implemented, the overlap of key research themes and authors, and the analytical techniques utilized in this fast-developing domain. Author examined 147 studies released from 2014 to 2020. They determined that although AI-driven systems have great potential to fulfill individual student requirements, there are currently few fully operational systems in place, and the mapping acts as an essential reference for upcoming research to enhance system design that addresses particular learning challenges.

## **2.6 User Attitudes, Acceptance & Behavioral Factors in E-Learning**

This study aimed to investigate how user attitudes toward Artificial Intelligence (AI) in e-learning particularly its impact on improving the Personal Learning Profile (PLP), Network (PLN), and Environment (PLE) influence the adoption process. The tasks performed in [18] included gathering data from e-learning participants and using PLS-SEM analysis to merge these ideas with the Technology Acceptance Model. They determined that the Personal Learning Environment (PLE) greatly influences both perceived utility and user-friendliness, with satisfaction and attitude eventually mediating the user's intention to persist with AI-driven e-learning systems.

This quantitative research aimed to explore the elements affecting the attitudes of students and teachers regarding the sustainable integration of e-learning, especially in developing nations. The study [19] included using a modified Technology Acceptance Model (TAM), which added elements such as mental acceptance and trust in the system, to examine the behavioral intentions of 367 educators and students. The authors determined that all fundamental TAM elements substantially influence the intention to engage in e-learning, with mental acceptance serving a vital moderating function. This emphasizes that organizations need to prioritize fostering positive

mindsets, tackling opposition, and resolving ICT skill and infrastructure gaps for sustainable e-learning achievement.

## **2.7 Cognitive Psychology & Neuropsychology-Driven Personalization**

The key focus of [20] systematic review is the ability of AI in e-learning to develop genuinely personalized learning experiences and adaptive assessment frameworks by integrating knowledge from Cognitive Neuropsychology (cognitive psychology that studies the relationship between the structure and function of the brain and specific psychological processes like memory, language, perception, and reasoning). The research finds that AI interventions informed by cognitive neuroscience are very effective at managing cognitive load and enhancing instructional difficulty, resulting in marked improvements in student performance, engagement, and motivation.

## **2.8 AI-Driven Motivation, Engagement & Management Education**

This interdisciplinary study of author [21] aimed to highlight the importance of implementing AI-driven personalized learning (AIPL) in management education and to align it with the principles of Self-Determination Theory (SDT). The effort undertaken involved empirical data-driven examination to show how AIPL positively impacts students' fundamental psychological needs autonomy, competence, and relatedness which serve as the motivators of intrinsic motivation and involvement. The authors determined that AIPL significantly influences management education, highlighting autonomy as a crucial element closely associated with enhanced academic performance (AP), confirming AI's essential role in intrinsically driving motivation for management student.

## **2.9 Personalized Feedback & Learning Behaviour Analytics**

The review [22] aimed to establish an analytical framework for classifying and summarizing the main characteristics and empirical findings of personalized feedback implementations in digital learning environments (DLEs). The focus of the conversation was on exploring the extent and impact of personalized feedback at the micro, meso, and macro levels of DLEs, examining the sources to which feedback is

tailored. The authors determined that although personalized feedback usually shows beneficial results, the sources utilized for customization are limited primarily to students' existing knowledge and learning behavior information. They support conducting future studies to investigate more comprehensive data sources such as emotional states, learning objectives, and personality characteristics to deliver more meaningful, theory-based feedback.

### **2.10 Emotion-Based Personalized Learning Systems**

The document [23] presents an Intelligent Personalized Learning System (IPLS) that employs a Takagi-Sugeno fuzzy inference engine to assess student frustration through data from the Learning Management System (LMS). Upon detecting signs of frustration, the system provides motivational messages grounded in Regulatory Fit Theory to enhance the learner's performance. The Takagi-Sugeno (T-S) Fuzzy Inference Engine (also known as the TSK model) is a powerful method in fuzzy logic for modeling complex, non-linear systems.

### **2.10 Machine-Learning-Based Adaptive & Recommendation Systems**

The area of discussion in [24] research is that automated detection of student Learning Styles (LSs) in Personalized Adaptive Learning (PAL) systems through the use of Machine Learning (ML) methods. The research determines that ML methods, especially Artificial Neural Networks (ANNs), are progressively successful in dynamically categorizing LSs based on student behavior, overcoming the shortcomings of static questionnaires and facilitating genuinely adaptive e-learning solutions.

The aimed to examine the existing research on Machine Learning (ML)-driven recommendation systems particularly utilized in the realm of e-learning. The discussion centered around categorizing various ML methods employed (e.g., collaborative filtering, content-based, hybrid models), the data sources used (e.g., student performance, behavior), and the general structure of these systems. The authors of [25] determined that although ML recommendation systems have significant promise in improving learning results through personalized support, there is still an absence of standardized assessment metrics and a necessity for future research to create more

efficient hybrid models that combine various data, such as social and emotional elements.

### **2.12 AI-Enabled Intelligent Assistants & Virtual Teaching Systems**

This study [26] aimed to present and confirm a new framework, the Artificial Intelligence-Enabled Intelligent Assistant (AIIA), intended to transform personalized and adaptive learning in Higher Education. The project entailed developing an interactive platform that leverages sophisticated Natural Language Processing (NLP) to produce course-specific resources, including tailored quizzes and flashcards, as well as to respond to student questions. The system is designed specifically to lighten the cognitive burden on learners. The authors determined that the AIIA system can greatly influence the development and assessment of Virtual Teaching Assistants (VTAs), thereby improving student learning results, involvement, and overall contentment.

### **2.13 Personalized Learning Models in Blended Learning Environments**

This integrative literature review [27] aimed to present a summary of personalized learning theory, technology, and contemporary practices in blended learning settings in Higher Education. The discussion centered on pinpointing particular technology models that effectively enable personalization. The authors recognized three essential technological frameworks digital badges, adaptive learning technology, and competency-based education that enable personalized learning routes. They determined that although these models demonstrate potential in transitioning education into a learner-centered approach, there is still a considerable deficiency in data-driven, independent research to thoroughly confirm their long-term impact on student learning results.

Table 1 Gap Analysis

<b>Paper</b>	<b>Research Outcome</b>	<b>Limitation</b>	<b>Research Gap</b>
[5]	Personalized Learning & Definitions Frameworks	Did not connect conceptual definitions to real-time user emotion data or performance metrics in web-based learning.	Lack of an applied framework linking emotional processing and personalized systems for live e-learning environments.
[6]	AI in Education and Technology Review	Limited focus on integration of emotional and behavioral indicators for real-time adaptation.	Gap exists for emotion-driven AI personalization in adaptive e-learning systems.
[7]	Trends in AI & Personalized Learning	No unified model connecting emotional and cognitive personalization.	Opportunity to integrate findings into a comprehensive adaptive learning framework.
[8]	Intelligent E-Learning Systems	Models were theoretical, lacked evaluation on real-time learner interactions.	Need for practical, real-time adaptive systems responsive to learner behavior.
[9]	AI-Based Personalized E-Learning Systems	It did not focus on lightweight, resourceefficient systems or explainability.	Requirement for computationally lightweight, explainable AI systems.

[10]	Adaptive Learning Frameworks	Lacked real-time emotion-based personalization evaluation.	Gap for practical, emotionally adaptive learning frameworks.
[11]	Mapping Adaptive Learning Systems	Few fully operational systems; no integration with real-time emotion detection.	Need for operational adaptive systems integrating emotions and behavior.
[12]	User Perception & Technology Acceptance	Did not assess effect of emotion-aware personalization on user satisfaction.	Gap in understanding perception changes with emotion-driven personalization.
[13]	Sustainable Adoption of E-Learning	Limited focus on emotional engagement and personalization.	Need frameworks linking adoption with emotional AI personalization.
[14]	Cognitive Neuropsychology & Approaches	Did not incorporate multi-parameter emotion signals in real-time.	Gap for cognitive and emotion-integrated adaptive learning.

[15]	AI for Management Education	Focused on psychological motivation, lacked real-time adaptive content.	Gap for AI systems providing live adaptive learning content with motivation support.
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[16]	Personalized Feedback in Digital Learning	Feedback sources limited to knowledge and behavior, ignoring emotions.	Gap for emotionaware personalized feedback frameworks.
[17]	Emotion-Based Personalized E-Learning	Limited to emotion detection, lacked adaptive content delivery integration.	Gap for systems that link emotion detection with real-time adaptive learning content.
[18]	Learning Styles Identification with ML	Did not incorporate real-time emotional signals.	Gap for ML-based systems combining learning styles and emotion for personalization.
[19]	ML-Based Recommendation Systems	Lack of standardized metrics and integration with emotional factors.	Gap for hybrid models combining ML recommendations with emotional and behavioral data.
[20]	Intelligent Assistants in HE	Focused on NLP and resources; minimal focus on emotional adaptation.	Gap for intelligent assistants incorporating emotion-driven adaptive personalization.
[21]	Blended Learning Personalization	Did not integrate real-time emotion or	Gap for blended learning systems
		adaptive behavior signals.	with live emotional and behavioral adaptation.

[22]	Personalized feedback framework in digital learning	Covers feedback; does not integrate emotional or stressaware interventions.	Emotional or stressaware interventions missing
[23]	Intelligent personalized learning system based on emotions	Specifically targets emotion-aware systems; needs more empirical studies and large-scale deployment.	More empirical studies and largescale deployment needed
[24]	Adaptive learning technologies using ML to identify learning styles	Technical adaptation focus; emotional/affective learning states not fully integrated.	Emotional/affective learning state integration missing
[25]	ML-based recommendation systems for e-learning	Early ML personalization: emotional engagement and adaptive content for stress not addressed.	Emotional engagement and stress-based adaptation missing
[26]	AI-enabled intelligent assistants for personalized learning in higher ed	Focuses on assistant systems; emotional content personalization is limited.	Emotional content personalization is limited
[27]	Learning technology models supporting personalization in blended learning	Broad models; lacks concrete guidelines for stress/emotionaware content design.	Guidelines for stress/emotionaware content design missing

Sentellect was uniquely created to close significant gaps noted in various research studies regarding personalized learning systems. The system directly tackled the shortcomings of current frameworks, like those mentioned in [5], [6], [8],[10], and [11], which did not provide an applied structure for connecting real-time emotional processing with adaptive systems for live e-learning settings. Additionally, Sentellect addressed the shortcomings in studies such as [16] and [19] by incorporating emotional and behavioral data into the recommendation and feedback creation process, advancing beyond sources restricted solely to knowledge and performance. The adoption of a lightweight, explainable AI (XAI) system addressed the demand mentioned in paper [9] for models that are transparent and computationally efficient. In the end, Sentellect created a fully functional, emotionally responsive learning system that features individualized assistance and openness, meeting the widespread research demand for such an all-encompassing platform as emphasized by [7] and [14].

## CHAPTER 3

### DESIGN AND METHODOLOGY

#### 3.1 Background

A Major leap forward in individualized learning is the use of emotion detection technologies into educational systems. Teachers can improve students' motivation, engagement, and learning outcomes by appropriately assessing and meeting their emotional needs [28]. The increasing significance of emotion-conscious educational systems can be evidenced by a large amount of research suggesting many different algorithms and models to identify the emotions of students and utilize the collected information to customize the learning process. On this basis, we too have created our own structure an emotion driven personalization algorithm that is specifically created to personalize the mathematics HSSC Part 2 curriculum of the Punjab Textbook Board. Our strategy is based on emotional cues to adjust the content difficulty, assistive feedback, and optimization of the learning process so that, every student obtains a unique and adaptable learning experience in accordance with their emotional and cognitive requirements.

#### 3.2 System Architecture

The system implements an integrated emotion-aware personalization model designed to adjust the Punjab Textbook Board mathematics curriculum to meet individual learner needs. The system starts by taking the responses from the dataset and featureengineering them to create a 30-dimensional input vector reflecting anxiety, depression, demographics, and behavioural indicators. This refined dataset is used to train a Random Forest classifier. The trained model produces a categorical stress profile: low, moderate, or high. This profile serves as the main emotional-state variable within the broader personalization system. After estimating stress levels, it eliminates the black box module by explaining the decision made by the AI, using XAI. These elements are combined in a personalization engine. The resulting recommendation layer connects students to suitable modules from the Punjab Textbook Board

mathematics HSSC Part 2 curriculum. This integrated approach improves the effectiveness of personalized learning and provides both cognitive and emotional support for students.

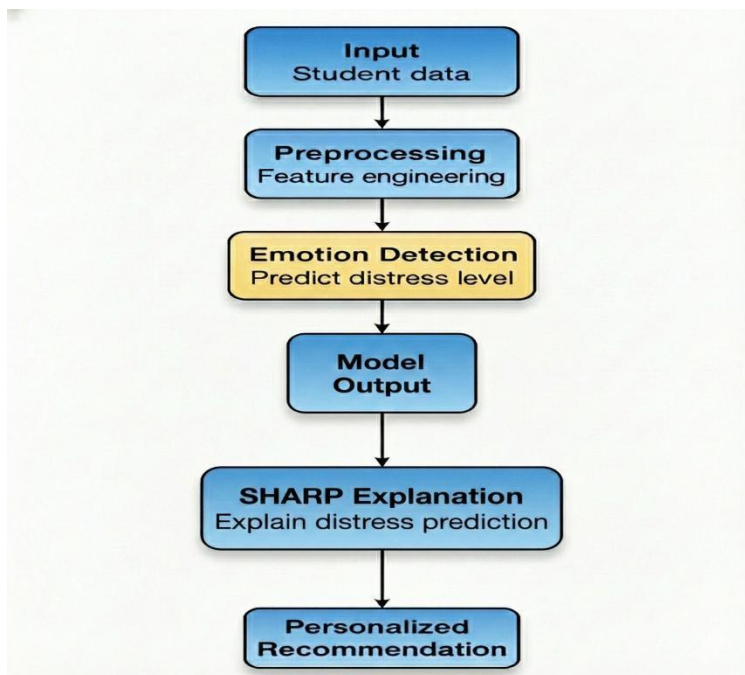


Figure 1 System Architecture Flowchart

### 3.2.1 Tool and Technology:

Table 2 Tools and Technology used

Category	Tools and Technology Used	Purpose
Python framework for integration	Python Flask	Web framework for building the application, managing server-side logic, and handling data flow between the frontend and models.

Recommendation & Explainability	XAI (Explainable AI)	Providing transparency for the suggested learning roadmap and recommendation advice, explaining <i>why</i> a particular path or suggestion was given to the student.
Machine Learning Model	Random Forest	Used for mood prediction (classifying stress levels as Low, Medium, or High) based on student data and emotional input.
Feature Engineering Insight	Feature Importance	Used to show which variables were most influential in the Random Forest model's mood prediction, enabling greater system transparency.
Chatbot	Gemini API	Integration with a Large Language Model Gemini API to power the Chatbot, providing interactive and intelligent learning/emotional support and guidance.
Database	SQLite	Persistent storage solution for structured data, including Student Profiles, Learning Paths, assessment results, and system logs.
Frontend / User Interface	HTML, CSS	For developing the student interface, displaying the learning path.

### 3.2.2 Product Perspective:

Sentellect is a web-based system that enhances traditional e-learning by introducing emotion recognition and adaptive content delivery. Unlike conventional platforms, which only assess academic performance, Sentellect considers both academic and emotional states of learners. The system architecture is divided into four main layers:

1. **User Interface Layer** – Dashboards for students.
2. **Application Layer** – Core services such as login, quizzes, reporting and chatbot.

3. **AI Layer** – Emotion recognition, personalized path generation, and explainable AI.

4. **Database Layer** – Storage of academic results, behaviour logs, quizzes, and reports.

### 3.2.3 Product Functions:

The following are the functionalities our web app is performing:

- **User Registration and Login:** Allow user to create account get register.
- **Initial Survey Assessment:** Collects information regarding the learner’s abilities, emotional states, preferences, and background to understand their initial capability level.
- **Emotional Recognition:** Detect student emotional stress level.
- **Personalized Learning Path Generation:** Creates a tailored learning route based on diagnostic results catering emotional state too.
- **Quizzes:** To track that user understandability.
- **Interactive Chatbot Support:** Provides a built-in AI chatbot to offer explanations, guidance, and assistance in study.
- **Progress Monitoring:** Tracking performance improvement, learning pace.

### 3.3 System Workflow:

The workflow diagram outlines the sequential process of user engagement with the system. It illustrates the progression of steps from logging in to completing tests, accessing tailored content, and checking performance reports. This diagram aids in illustrating system behavior and highlights decision points, concurrent activities, and logical sequences. Understanding user journeys and automating systems is crucial.

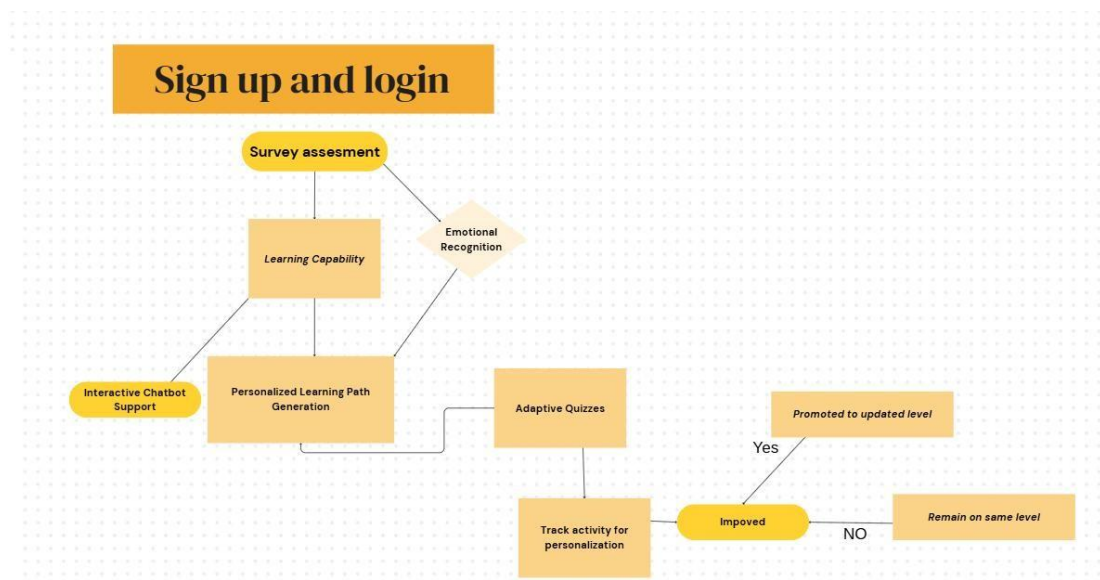


Figure 2 System Workflow

### 3.3.1 Component Diagram for Sentellect functionalities:

This diagram illustrates the main components of the Sentellect system and their interactions. It shows how the frontend, backend, chatbot service, explainability module, and database communicate to deliver adaptive content and responses to the student.

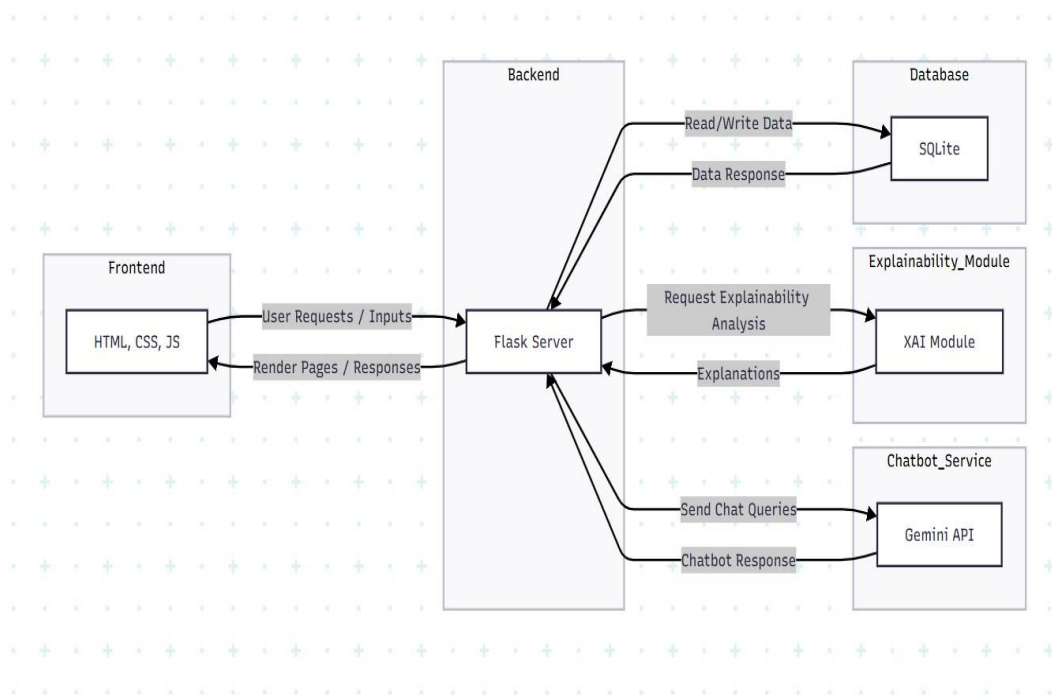


Figure 3 Component Diagram

### 3.3.2 Sequence Diagram:

This sequence diagram depicts the communication between a student and an adaptive learning system that includes a System, Chatbot, AI Model, and XAI Engine.

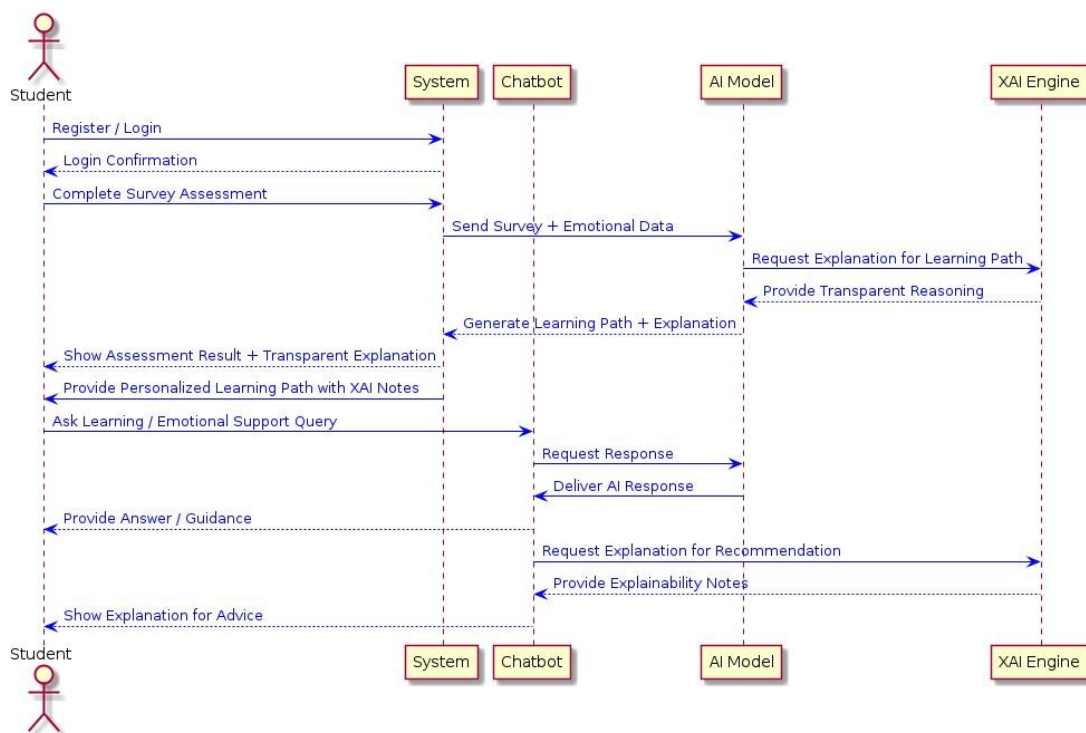


Figure 4 Sequence Diagram of Sentellect

- The procedure starts with the student signing up/logging in and finishing an evaluation. This Emotional Data + Survey is transmitted to the AI Model through Chatbot.
- The AI Model asks for and obtains a Transparent Reasoning for a Learning Path from the XAI Engine, subsequently creating the Personalized Learning Path + Explanation.
- The System shows the Assessment Outcome + Clear Explanation and the customized learning path along with XAI Notes to the Student.
- When the Student poses a Learning / Emotional Support Question, the Chatbot solicits and provides an AI Response and then seeks an Explanation for Recommendation from the XAI Engine to present the Explanation for Advice to the student.

### 3.3.3 Class Diagram:

This class diagram depicts the framework of the Sentellect System, responsible for handling Students and creating a Learning Path for each based on their Student Profile. The system employs an AI-Model and XAI-Engine to examine student data, develop personalized learning trajectories, and offer clear explanations for the guidance and suggestions provided via a Chatbot interface.

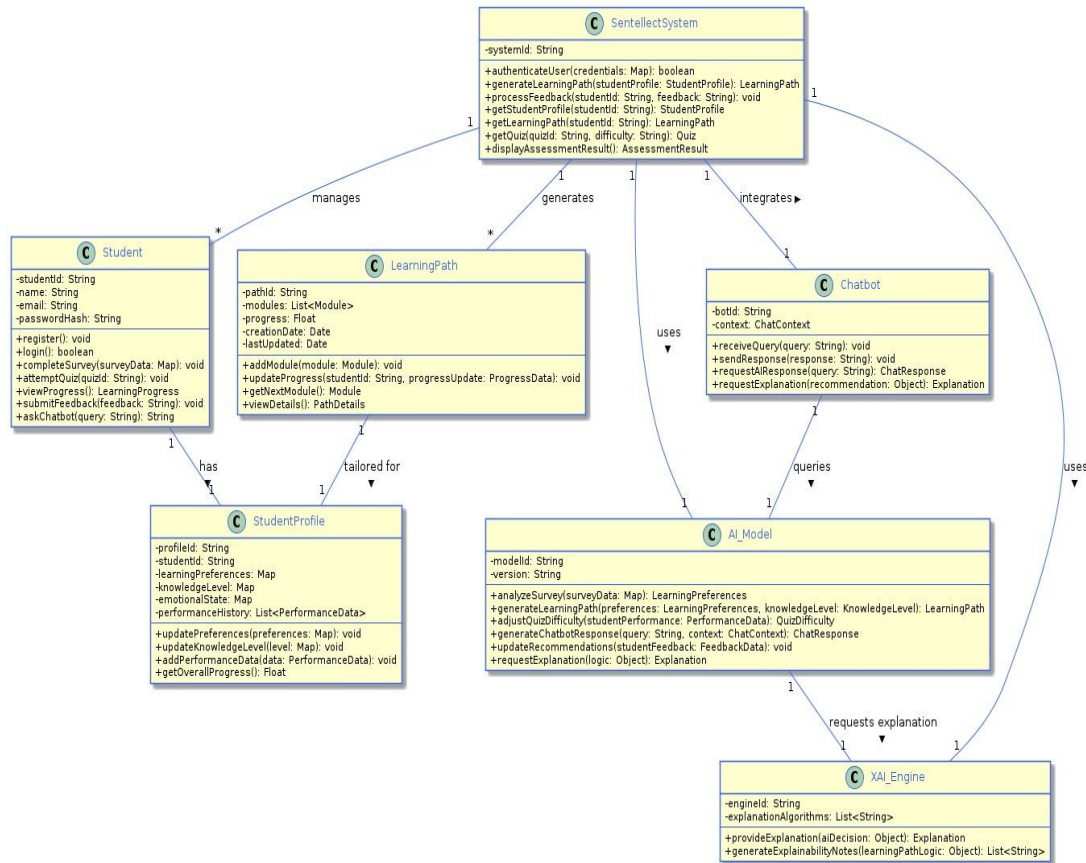


Figure 5 Class Diagram

### 3.3.4 User Flow Diagram of Sentellect System:

This flowchart illustrates the step-by-step journey of a student using the Sentellect system. It shows the process from login/signup, completing surveys, mood and stress prediction, accessing chapters and quizzes, interacting with the AI chatbot and XAI module, to tracking progress. The diagram highlights how the system guides students through adaptive learning and support.

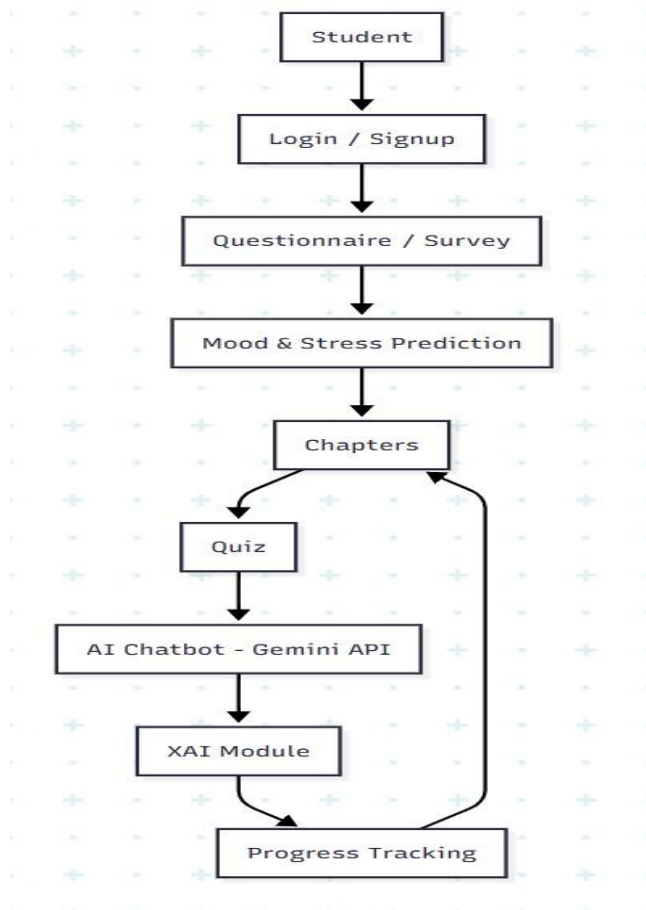


Figure 6 User Flow Diagram

3.4 Software Testing:

Table 3 Software Testing

Test Case ID	Module	Test Description	Test Inputs	Expected Output	Actual Result	Status
TC-01	User Registration	Verify new user registration	Name, Email, Password	Account created	As Expected,	Pass
TC-02	User Registration	Reject duplicate email	Existing Email	Error message	As Expected,	Pass

TC-03	Login	Valid login	Email + Password	Redirect to dashboard	As Expected,	Pass
TC-04	Login	Invalid login	Wrong password	Error shown	As Expected,	Pass
TC-05	Survey Assessment	Survey loads correctly	—	Questions displayed	As Expected,	Pass
TC-06	Survey Assessment	Verify survey saved	Responses	Stored & sent to model	As Expected,	Pass
TC-07	ML Model	Predict stress level	Survey vector	Low/Moderate/High	As Expected,	Pass
TC-08	XAI Engine	Show model explanation	Predicted class	Feature importance	As Expected,	Pass

TC-09	Learning Path	Generate personalized path	Stress label	Correct modules assigned	As Expected,	Pass
TC-10	Content System	Load chapters	Chapter click	Content displayed	As Expected,	Pass
TC-11	Mood Adaptation	Trigger intervention popup	Long dwell time / wrong answers	Popup shown	As Expected,	Pass

TC-12	Chatbot	Chatbot replies	User question	Helpful response	As Expected,	Pass
TC-13	Chatbot + XAI	Explain chatbot advice	Student query	Explanation added	As Expected,	Pass
TC-14	Quiz	Load quiz	Attempt quiz	Quiz displayed	As Expected,	Pass
TC-15	Quiz	Save quiz score	Quiz answers	Score stored	As Expected,	Pass
TC-16	Performance	Update progress	Module complete	Progress updated	As Expected,	Pass
TC-17	Database	Store data	Any data	Saved in SQLite	As Expected,	Pass
TC-18	UI Navigation	Navigate pages	Button click	Correct page loads	As Expected,	Pass
TC-19	Logout	Session end	Logout click	Redirect login	As Expected,	Pass
TC-20	Error Handling	Server disconnect	Timeout	Error message	As Expected,	Pass

## CHAPTER 4

### DATA AND EXPERIMENTS

#### 4.1 Dataset:

For the implementation of this algorithm, the DASSR dataset is used. It contains responses to the Depression Anxiety Stress Scales (DASS-21) 42 questions, which are standardized self-report items used to quantify emotional distress. It provides validated numerical scores for depression, anxiety, and stress.

##### 4.1.1 Dataset validation:

This study uses a public DASS-21 dataset from Kaggle, collected through OpenPsychometrics.org from 2017 to 2019. The DASS-21 is a validated questionnaire for measuring self-reported depression, anxiety, and stress. However, this dataset is a non-validated, self-selected convenience sample. Despite this limitation, its large size makes it suitable for our goal of developing and evaluating a computational model to predict distress levels.

#### 4.2 Feature Engineering:

Out of the 42 questions, 28 questions with higher impact were selected. In which 14 questions were from the depression scale, and 14 questions were from the stress scale. Each question is fed to the model to predict and is given an alphanumeric name. Following are the questions and their names.

##### 4.2.1 Depression Scale:

- (Q3A) I couldn't seem to experience any positive feeling at all.
- (Q5A) I found it difficult to work up the initiative to do things.
- (Q10A) I felt that I had nothing to look forward to.
- (Q13A) I felt sad and depressed.
- (Q16A) I felt that I had lost interest in just about everything.

- (Q17A) I felt I wasn't worth much as a person.
- (Q21A) I felt that life was meaningless.
- (Q24A) I couldn't seem to get any enjoyment out of the things I did.
- (Q26A) I felt downhearted and blue.
- (Q31A) I was unable to become enthusiastic about anything.
- (Q34A) I felt I was worthless.
- (Q37A) I could see nothing in the future to be hopeful about.
- (Q38A) I felt that life wasn't worthwhile.
- (Q42A) I found it difficult to work up the initiative to do things.

#### **4.2.2 Anxiety Scale:**

- (Q2A) I was aware of dryness of my mouth.
- (Q4A) I experienced breathing difficulty.
- (Q7A) I had a feeling of shakiness (e.g., legs going to give way).
- (Q9A) I found myself in situations that made me so anxious I was most relieved when they ended.
- (Q15A) I had a feeling of faintness.
- (Q19A) I perspired noticeably (e.g., hands sweaty).
- (Q20A) I felt scared without any good reason.
- (Q23A) I had difficulty in swallowing.
- (Q25A) I was aware of the action of my heart in the absence of physical exertion.
- (Q28A) I felt I was close to panic.
- (Q30A) I feared that I would be "thrown" by some trivial but unfamiliar task.
- (Q36A) I felt terrified.
- (Q40A) I was worried about situations in which I might panic and make a fool of myself.
- (Q41A) I experienced trembling (e.g., in the hands).

In addition to the questions, 2 of the demographic features were selected, which are age and gender.

#### **4.2.3 Feature Importance:**

The feature importance analysis further validated this selection by identifying key emotional indicators. Feature importance analysis was conducted using the Random Forest's impurity-based ranking method, which highlights how much each feature contributes. This procedure made sure the model only used the most psychologically significant and discriminative characteristics, which led to a more precise, lightweight, and comprehensible emotion-aware personalization system. The following figure shows the impact level of the top 15 features.

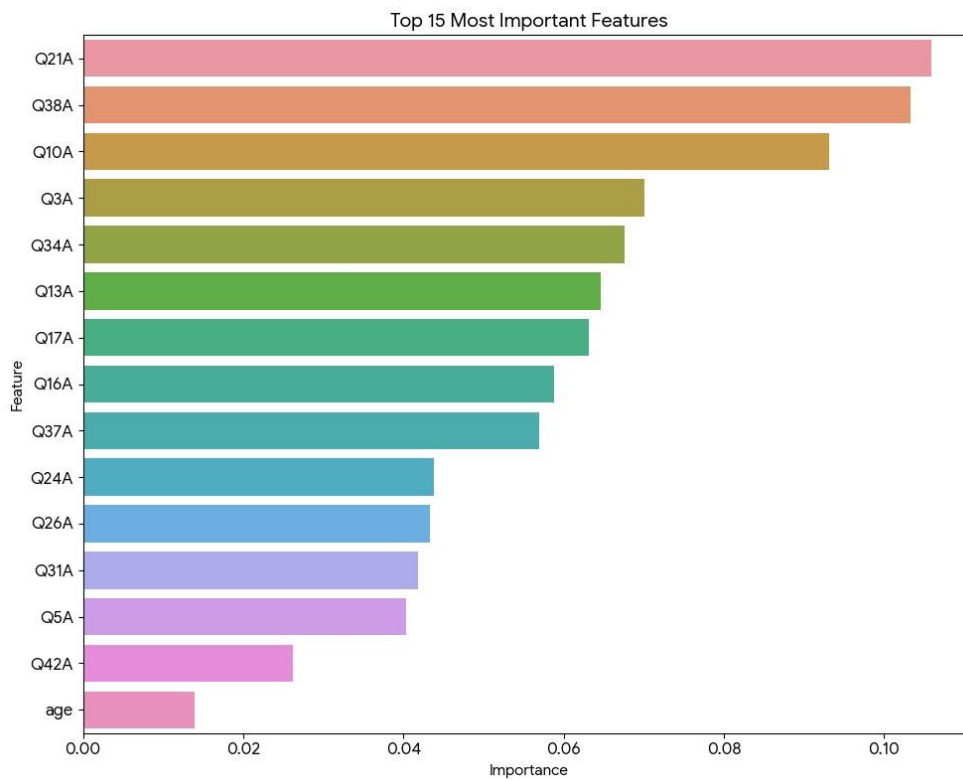


Figure 7 Feature Importance

### 4.3 Model Training:

#### 4.3.1 Random Forest Classifier:

A Random Forest is an ensemble learning approach. The fundamental idea behind this algorithm is the construction of small Decision Trees (DTs), which are considered computationally cheap. Multiple small and weak DTs are built in parallel and are then integrated to create strong learners by considering a majority vote [2]. The core predictive model in the suggested system is the Random Forest classifier, which uses

30 carefully chosen features from the DASS-R dataset to estimate a student's emotional distress. Its ensemble of decorrelated decision trees manages noisy or correlated questionnaire items, reduces overfitting, produces stable predictions, and captures intricate nonlinear relationships. Along with academic grades and a diagnostic math quiz score, the predicted stress level is fed into the personalization layer to modify the difficulty of the lesson and the progression of the content. Random Forest is therefore the foundation for emotion-detection, allowing for data-driven, affect-sensitive curriculum personalization in mathematics.

$$\begin{aligned}
 D_t &\leftarrow \text{bootstrap}(D) \\
 F &\leftarrow \text{random subset of } m \text{ features} \\
 s^* &= \arg\max_{s \in S_j, j \in F} \Delta C(s, D_t) \\
 Gini &= 1 - \sum_{k=1}^K p_k^2 \\
 Entropy &= - \sum_{k=1}^K p_k \log_2(p_k) \\
 \Delta C &= C(\text{parent}) - \sum_{c \in \{L, R\}} \frac{|D_c|}{|D|} C(D_c) \\
 \hat{y} &= \arg\max_{k \in \{1, \dots, K\}} \sum_{t=1}^T 1\{f_t(x) = k\}
 \end{aligned}$$

The Random Forest algorithm begins with a dataset of feature vectors and labels. For each tree, it creates a new training set by bootstrap sampling, meaning data points are selected randomly with replacement. During tree construction, only a random subset of features is considered at each split, and the best split is chosen based on impurity reduction using measures like Gini impurity or entropy. These impurity measures evaluate how well a split separates the classes. After training all trees, each one predicts a class for a new data point. The final prediction is made using majority voting, where the class with the most votes becomes the output. This process improves accuracy, reduces overfitting, and makes the model more robust.

#### 4.3.2 Model Training Process:

The proposed framework was evaluated to assess its effectiveness in detecting the distress level. The mental health dataset of DASSR was used to train the framework based on the Random Forest Classifier with 28 question scores on the issue of psychological questions and two demographic features that define the severity of depression. The data underwent a considerable amount of preprocessing (scale correction, one-hot encoding, normalizing, and stratification of the data) and the Random Forest model was trained on the classification of the multi-class depression severity with the constraints of being a low-level model (Low, Moderate, High).

#### 4.4 Model Evaluation:

Model performance was quantitatively assessed using four standard metrics:

- **Accuracy:** The proportion of correctly predicted instances.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Measures the model's overall accuracy by dividing the number of correctly predicted observations by the total number of observations.

- **Precision:** The ratio of true positives to all predicted positives.

$$Precision = \frac{TP}{TP+FP}$$

It shows how many predicted positive cases are true.

- **Recall (Sensitivity):** The ratio of true positives to actual positives.

$$Recall = \frac{TP}{TP+FN}$$

Shows how many actual positive cases that the model accurately identified.

- **F1-Score:** The harmonic meaning of precision and recall, offering a balance between the two metrics.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

##### 4.4.1 Model Performance Matrix:

The Random Forest was very discriminative with a quality (precision) of 96.60% on the test set, an average weighted precision of 0.97, an average weighted recall of 0.97

and an average weighted F1-score of 0.97 demonstrating that the Random Forest could classify data at an exceptionally high level across its three classes.

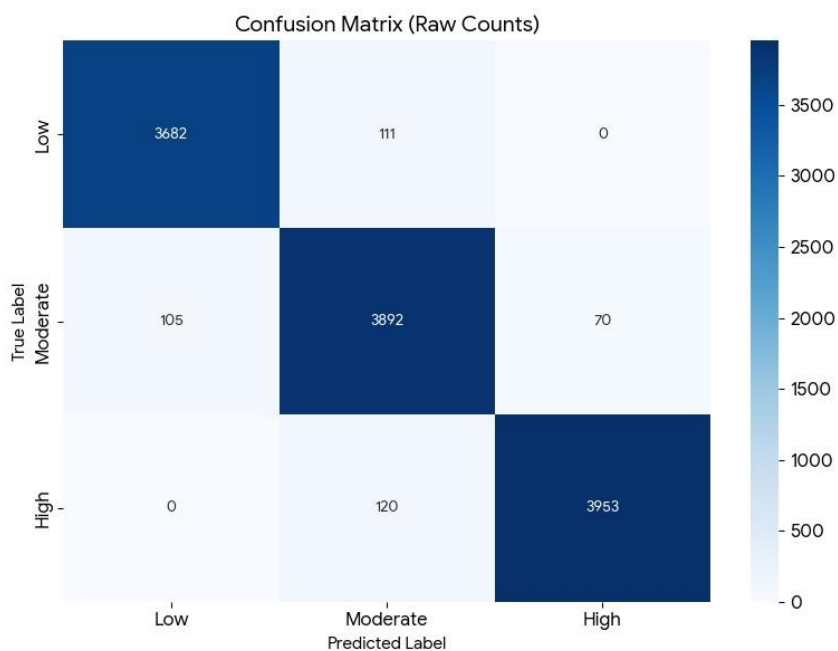
The following table shows the performance measures recorded using the formula for precision, recall, F1 score, and accuracy.

Table 4 Model Performance Measures

	precision	recall	f1-score
High	0.98	0.97	0.98
Low	0.97	0.97	0.97
Moderate	0.94	0.96	0.95
accuracy	-	-	0.97
macro avg	0.97	0.97	0.97
weighted avg	0.97	0.97	0.97

#### 4.4.2 Confusion Matrix:

The Confusion Matrix revealed that the model of the Random Forest had the best performance with the total accuracy of 96.60% on the hold-out test set.



### Figure 8 Confusion Matrix of Random Forest

The model was near-perfectly discriminating on the extreme levels of severity and correctly identified 97% of both the Low and the High cases and this is an outcome shown in the great recall scores. The confusion was only slightly evidenced in the moderate class with a precision of 0.94, suggesting that the model was, in some cases, confusing patients at one extremity with patients on the other end of the depression severity scale; however, high F1-scores (0.95 and above) indicate the model had a high predictive quality and feasible classification of patients spread across the entire range of depression severity.

#### **4.5 Model Performance Comparison:**

The overall model optimization procedure that was carried out on the DASSR data consisted of a critical sequence of steps that greatly improved the predictive performance. The original naive Bayes model was based on 42 questions to predict 5 severity classes with the initial accuracy of 72.92%. In Model 1 (85.26%), the simplification of the classification problem into five classes made into three more general classes (the categories of Low, Moderate, and High) was the first significant change that was made. Model 2 (96.08%), which was the result of the critical choice by updating the algorithm used to the more powerful Random Forest Classifier, follows the first gain. Further models concentrated on features refinement: although it has a low lift, Model 3 (96.24) with all 42 questions including the demographics is the most complete model, the final and most efficient is Model 4 (96.60): with the judicious removal of noise and redundant features (14 of the Stress questions and the demographic of education), it produces a powerful, lean predictor using the 28 core Depression and Anxiety questions and a simple set of demographics.

Table 5 Model Comparison

Model	Features Used	Target Classes	Accuracy
Original Naive Bayes	42 Questions	5 Classes	72.92%
Model 1: Naive Bayes	42 Questions	3 Classes	85.26%
Model 2: Random Forest	42 Questions	3 Classes	96.08%
Model 3: Random Forest	42 Questions + Demographics	3 Classes	96.24%
Model 4: Random Forest	28 Questions + Demographics	3 Classes	96.60%

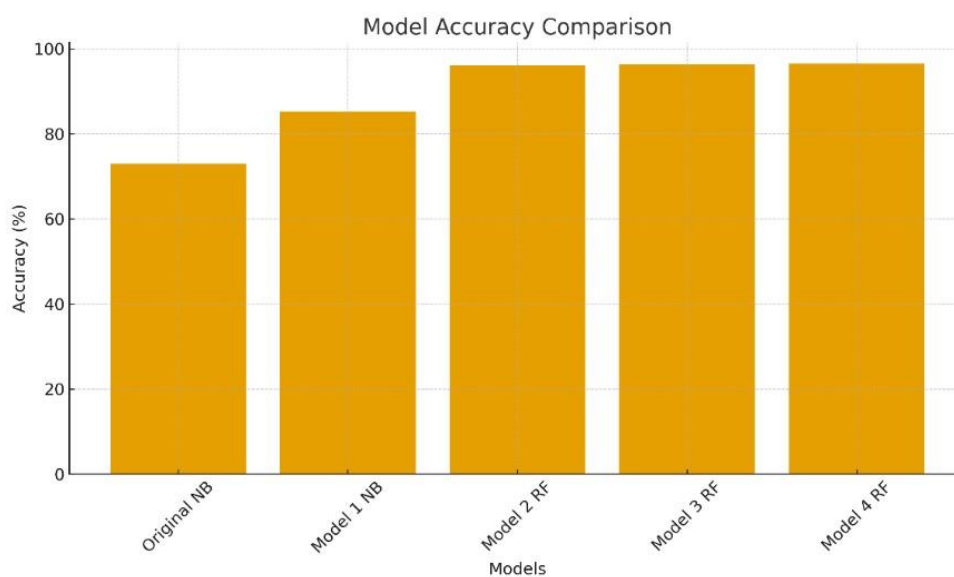


Figure 9 Bar chart for model performance comparison

Random Forest was selected as the best model due to its superior generalization on data, balanced precision, recall and all accuracy measures and reduced overfitting. Furthermore, it has higher potential for transparent and accurate prediction with higher model performance.

## CHAPTER 5

### 5.1 RESULTS AND DISCUSSIONS

#### 5.2 Frontend User Interface:

The successful execution is done, the Sentellect web application is completely developed, showcasing its potential as an adaptive learning platform. The application effectively delivers customized learning material and a relevant roadmap designed to meet the unique needs of each individual student. Below this is the core screen available in our web app.

##### 5.2.1 Main Screen:

The landing page of the web application. It features the system name, Sentellect and provides login and signup button for registration in app.

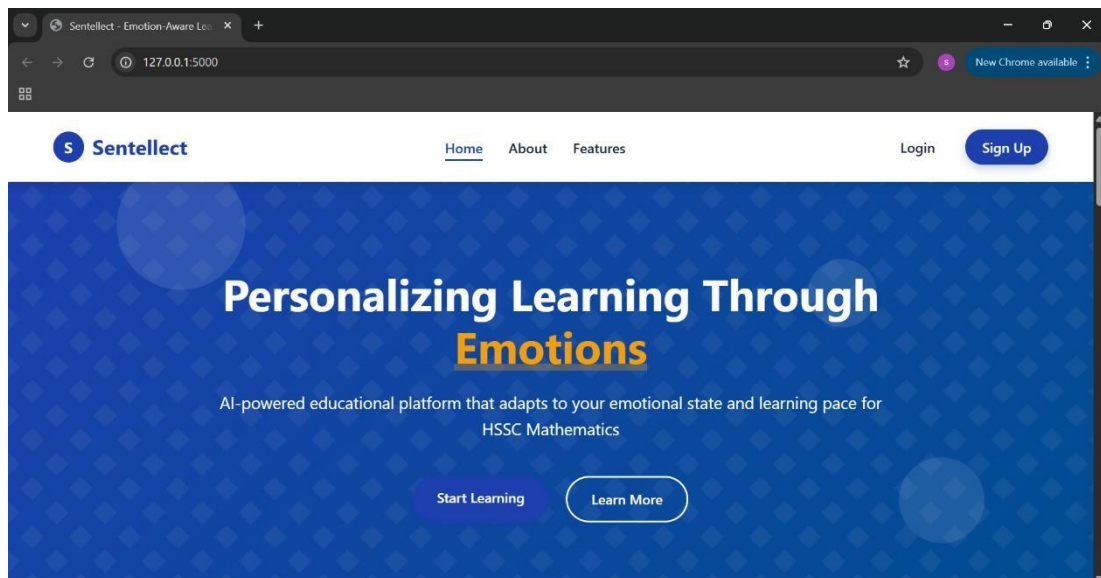


Figure 10 Main Screen

### 5.2.2 Sign Up Screen:

This screen shows to create an account and get register in Sentellect learning platform. Fields are for collecting key student data, including Full Name, Email Address, Phone Number, and Matric Result (%).

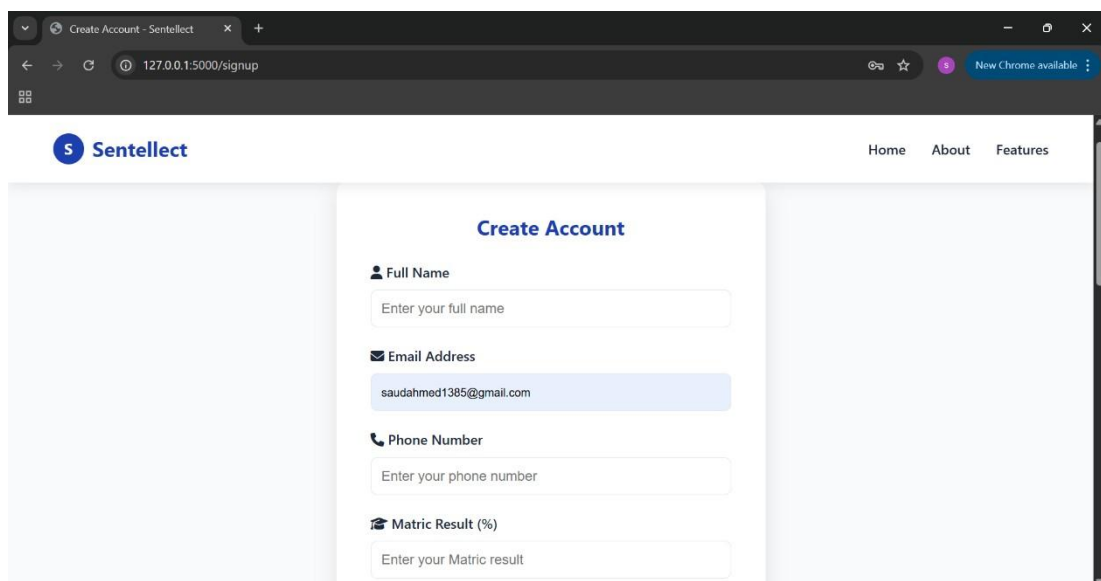


Figure 11 Signup Screen

### 5.2.3 Login Screen:

The authentication screen for existing users. Fields are for Username (Email) and Password to allow students to securely access the system.

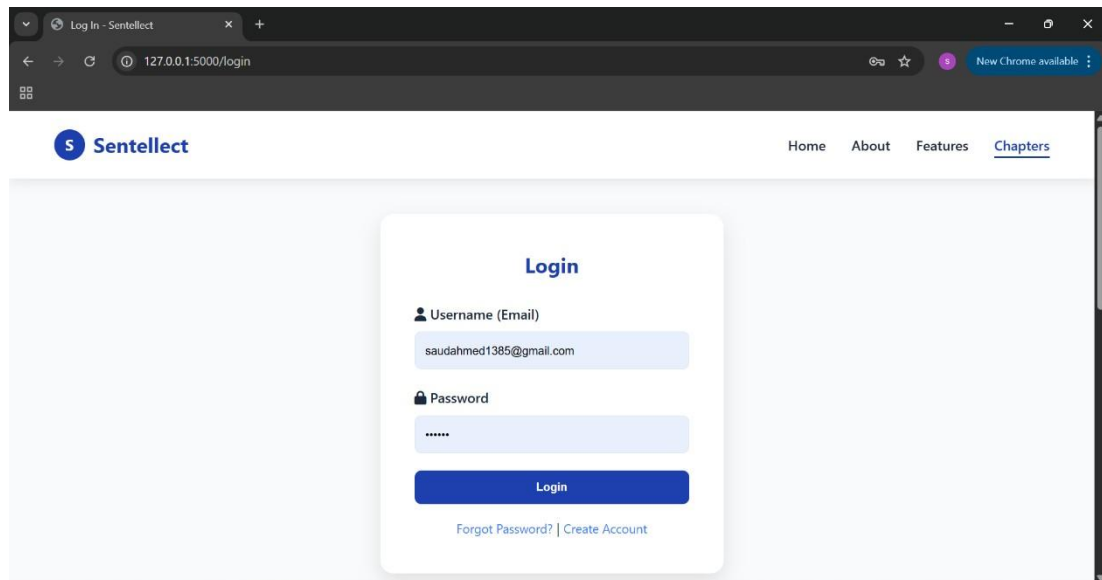


Figure 12 Login Screen

### 5.2.4 Feature & About:

The field in the below screen collects the demographic data of age and gender respectively.

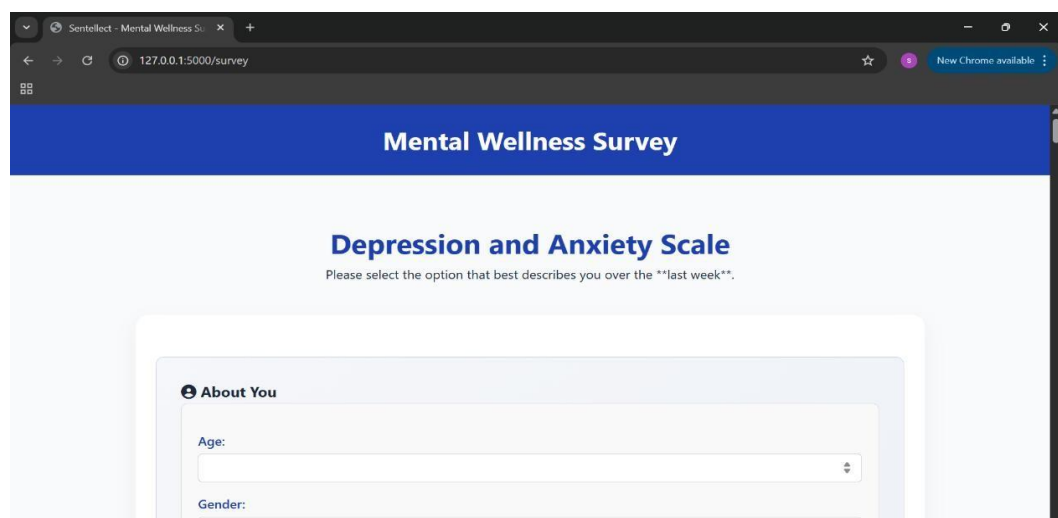


Figure 13 Feature and About

### 5.2.5 Survey Assessment:

The survey to assess the student learning capability and emotional state for providing them a respective learning content to each student according to their learning pace.

Sentellect - Mental Wellness Su

127.0.0.1:5000/survey

New Chrome available

#### Questions

1. I couldn't seem to experience any positive feeling at all.

0 - Never

1 - Sometimes

2 - Often

3 - Almost Always

2. I found it difficult to work up the initiative to do things.

0 - Never

1 - Sometimes

2 - Often

Figure 14(a) Survey Assessment

Sentellect - Mental Wellness Su

127.0.0.1:5000/survey

New Chrome available

#### Questions

7. I felt that life was meaningless.

0 - Never

1 - Sometimes

2 - Often

3 - Almost Always

8. I couldn't seem to get any enjoyment out of the things I did.

0 - Never

1 - Sometimes

2 - Often

3 - Almost Always

Figure 14(b) Survey Assessment

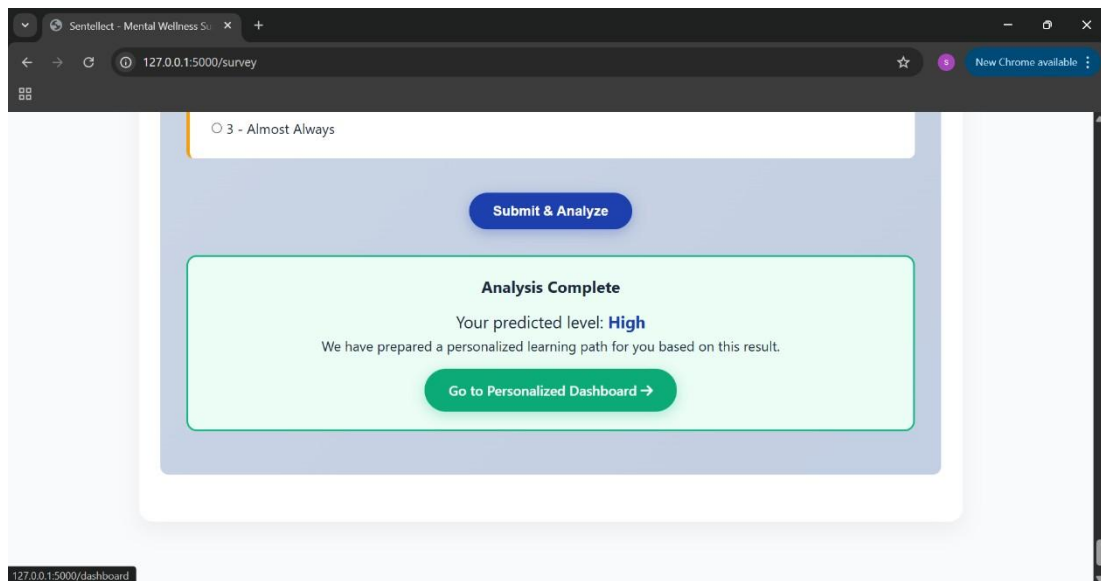


Figure 14(c) Survey Assessment

### 5.2.6 Dashboard:

The post-assessment screen that shows the student stress level based on above survey results. Welcomes the student, displays their personalized path based on their distress level, and includes an XAI explanation.

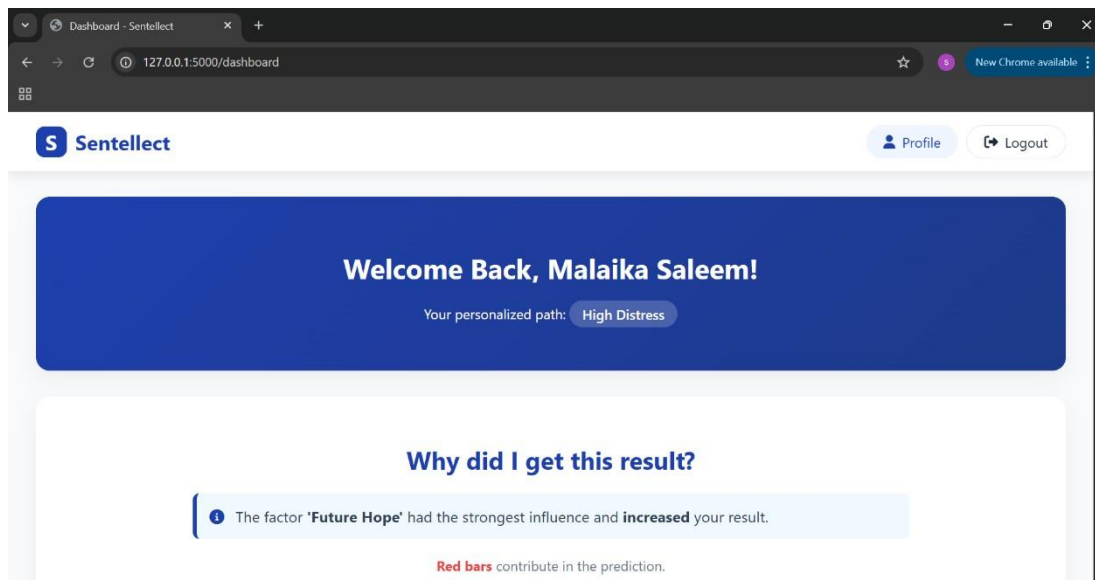


Figure 15 Dashboard

### 5.2.7 Modules:

These are the modules we are offering. The learning roadmap display showing progress and next steps.

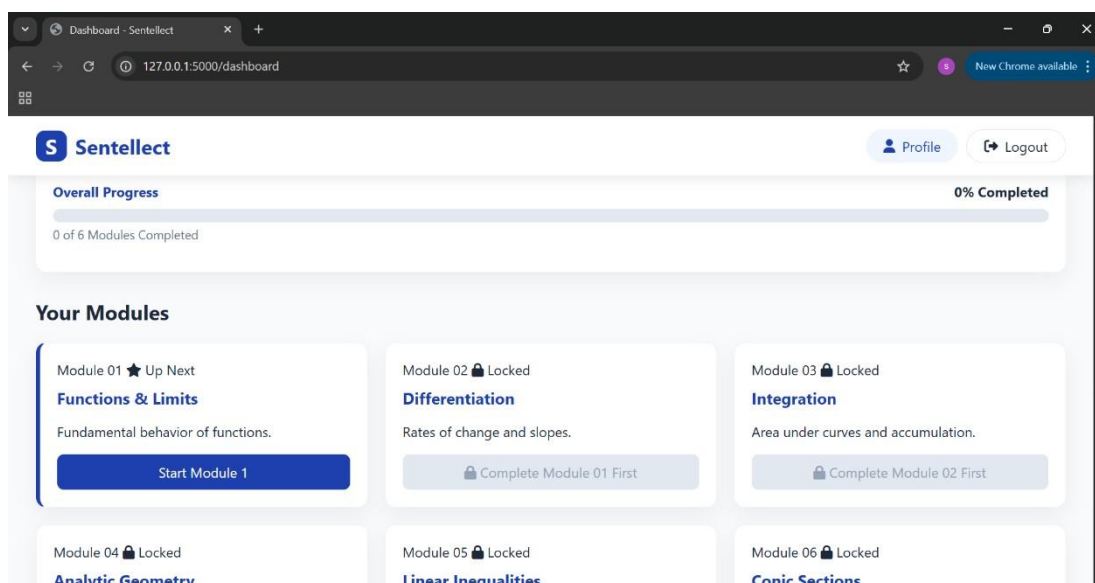


Figure 16 Modules

## 5.2.8 Offered Learning Content:

A screen where student accesses the learning material. The chapter student must do.

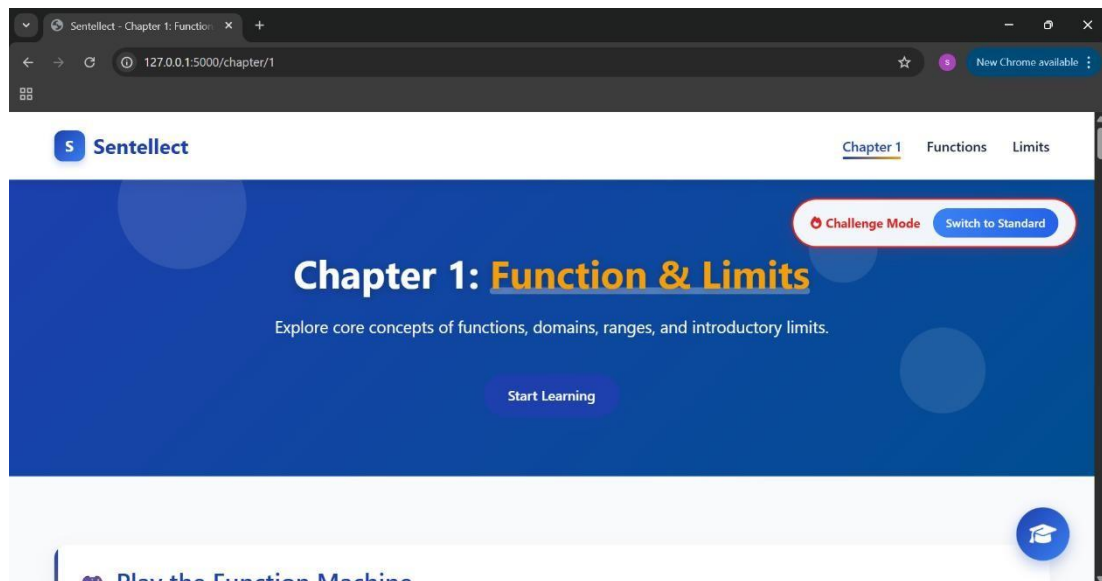


Figure 17 Offered Learning Content

## 5.2.9 Adoption according to mood:

The real-time, context-sensitive intervention pop-ups after analyzing the student adoption performance.

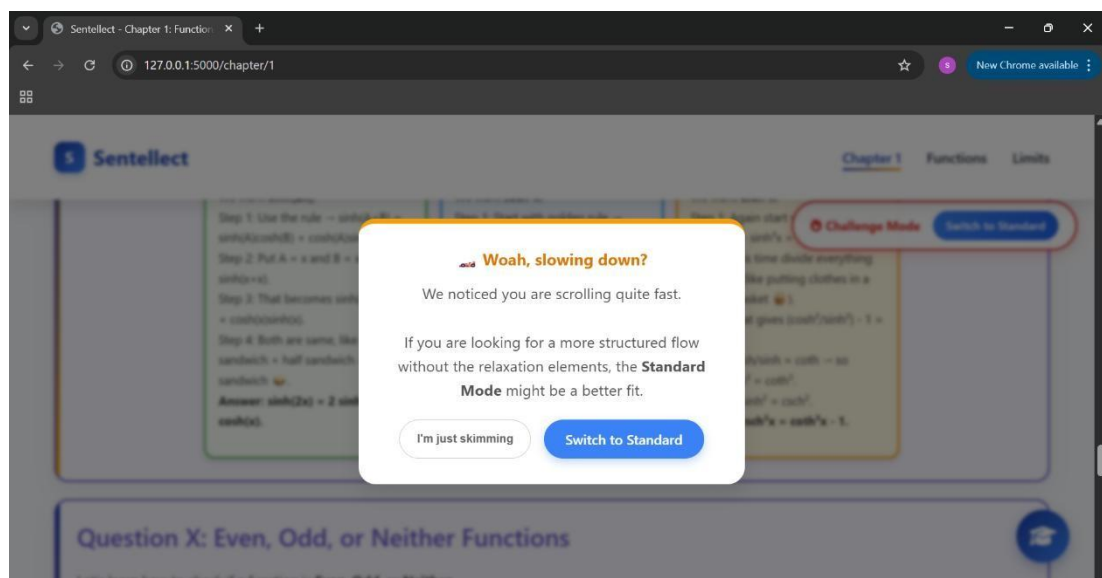


Figure 18(a) Trigger for Scrolling Fast

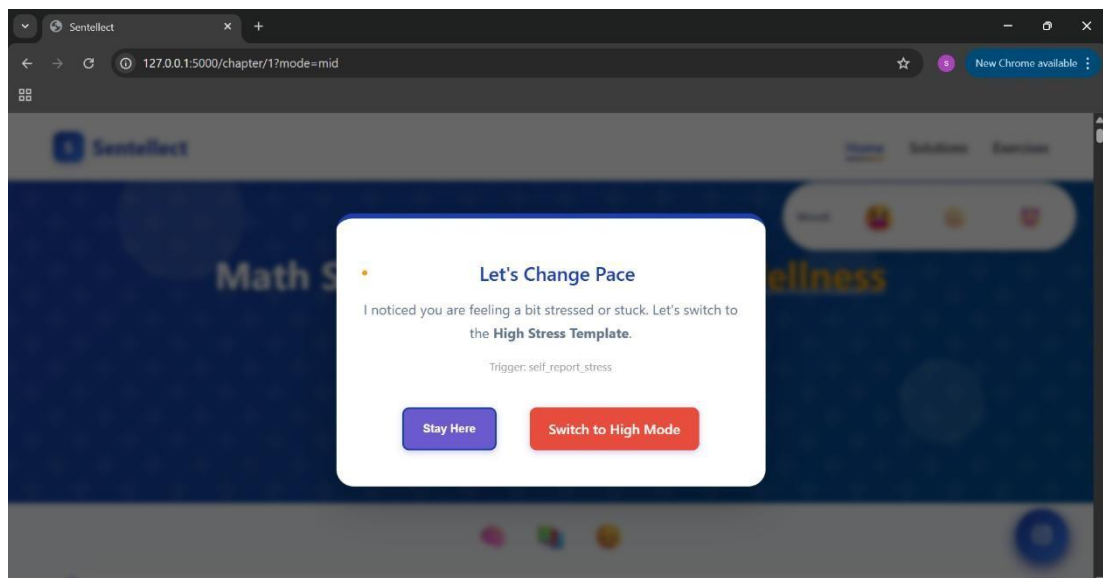


Figure 18(b) Self report Stress

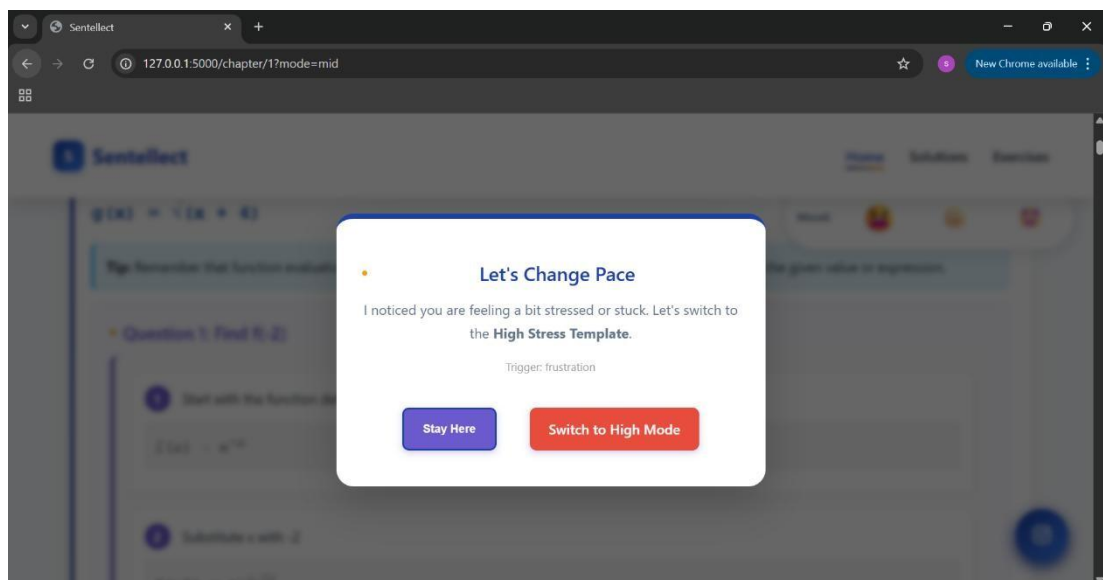


Figure 18(c) Trigger Frustration

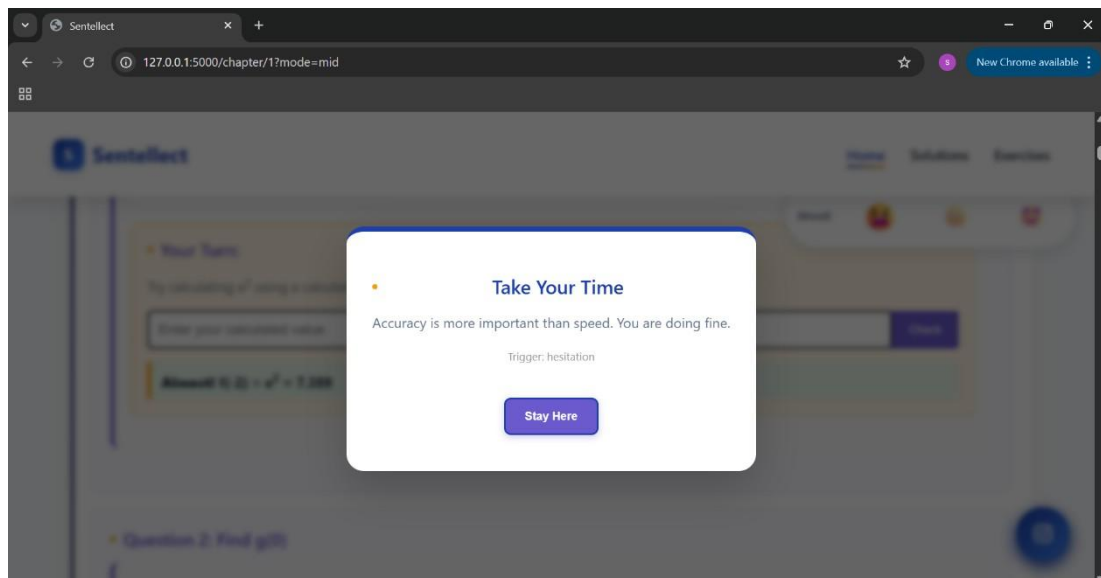


Figure 18(d) Trigger Hesitation

### 5.2.10 Performance Track:

This screen confirms the module completion and updating system progress.

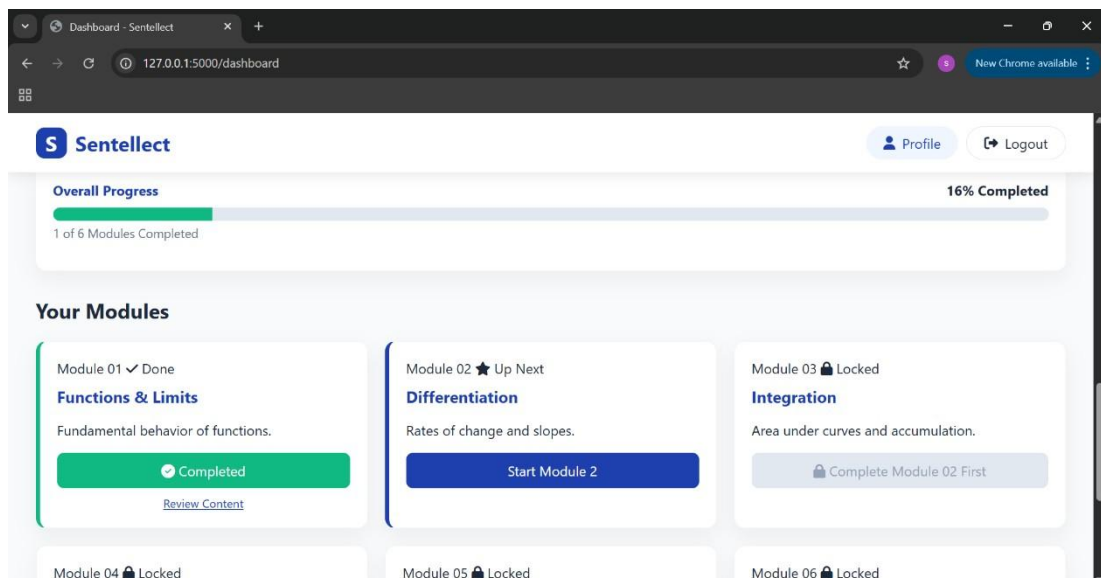


Figure 19 Performance Track

### 5.2.11 Quizzes:

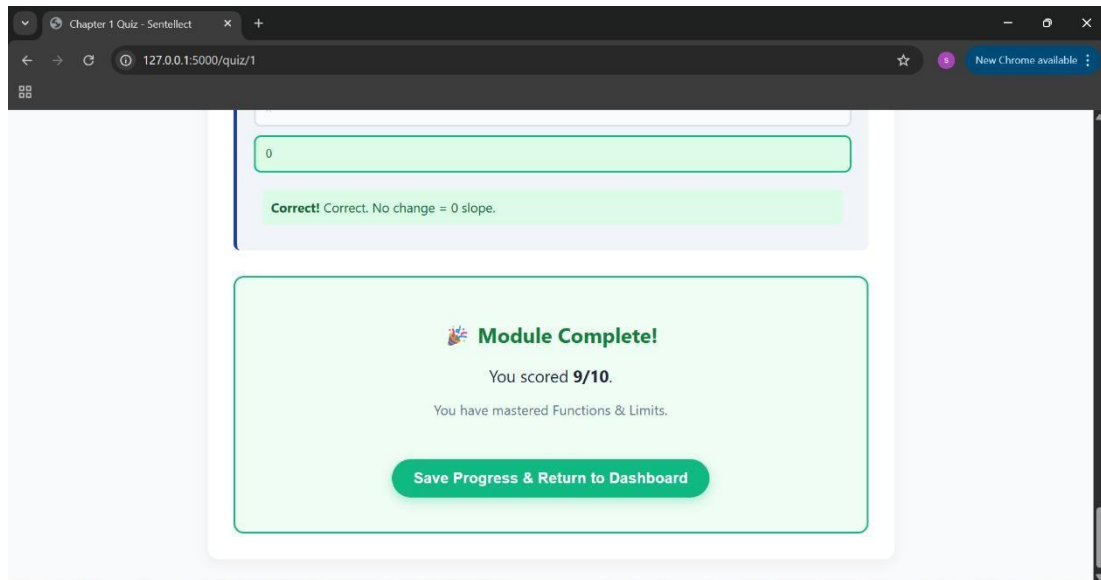


Figure 20 Quizzes

### 5.3 Discussion:

This study has notable, real-world significance, as it directly addresses the development of a highly accurate machine-learning model for predicting student depression severity related to early intervention and resource optimization within educational and public health systems. The significant advantage is early detection and triage; the 96.60% accuracy model can be easily embedded in digital wellness screenings, to provide an accurate, reliable, and scalable way to instantly classify students at Low, Moderate, or High risk. This mechanism lets mental health professionals immediately prioritize limited resources by directing those resources to students at High risk needing urgent clinical follow-up, while helping to distinguish Low risk students, who only need prevention.

Additionally, by relying on a combination of factors such as specific psychological symptoms and basic demographics, the model provides evidence-based recommendations for policy makers; the model assists them to identify which student groups are most at risk and design targeted and effective interventions that are inexpensive, for example, providing workshops on financial literacy or reducing academic workloads, rather than relying on broad or generalized programs.

## CHAPTER 6

### 6.1 CONCLUSION AND RECOMMENDATIONS

#### 6.1.1 Conclusion

The Sentellect initiative achieved the development of an innovative adaptive learning system that combines emotional intelligence with tailored content distribution, advancing past conventional uniform education methods. Through the precise forecasting of student distress levels (Low, Moderate, High) employing a Random Forest model with an accuracy of 96.60%, the system showcased a dependable ability to prioritize and initiate interventions according to a student's mental condition. This essential emotional information, along with cognitive abilities, fuels the creation of a customized learning pathway for 12th-grade Mathematics. Incorporating an Explainable AI (XAI) engine along with a Chatbot powered by LLM guarantees transparency in recommendations and provides ongoing, empathetic assistance, resulting in a learning experience that is both intelligent and focused on human values, fostering trust. The completed web application, developed using Python Flask and front-end technologies, demonstrates the viability of creating a highly adaptable, supportive, and context-sensitive educational platform.

In conclusion, Sentellect effectively tackles significant research gaps by explicitly connecting emotional states to educational personalization, demonstrating AI's capacity to foster nurturing learning atmospheres that emphasize mental health along with cognitive growth. Future efforts should aim at broadening the curriculum scope and incorporating more intricate real-time behavioral elements (such as dwell time and click patterns) to enhance emotional detection precision and widen the spectrum of adaptive interventions. The developed framework offers a solid base for advanced intelligent tutoring systems that are crucial for boosting student engagement, minimizing cognitive overload, and enhancing educational results in a digital age.

## **6.2 Future Recommendations:**

To improve Sentellect effectiveness, scalability, and resilience, the subsequent future suggestions are put forward:

- **Expansion in PTB Curriculum:**

Broaden the system's content and customization framework to encompass more classes and subjects included in the Punjab Textbook Board (PTB) curriculum.

- **Offline Capability:**

Establish local data storage and processing to allow offline access to content and quiz completion for students with restricted or inconsistent internet connectivity, synchronizing data once the connection is reestablished.

- **Enhanced Emotional Detection:**

Incorporating strategy for emotion identification, utilizing real-time facial recognition (evaluating micro-expressions for frustration, focus, and confusion).

- **Mobile App:**

The model can be integrated into a mobile application for further convenience. This would make the system more portable.

## REFERENCES

- [1] Hassouna, D. H. A., Khedr, A. E., Idrees, A. M., & ElSeddawy, A. I. (2020). Intelligent personalized system for enhancing the quality of learning. *Journal of Theoretical and Applied Information Technology*, 98(13), 2199-2213.
- [2] Holmes, W., Anastopoulou, S., Schaumburg, H., & Mavrikis, M. (2018). Technology-enhanced personalised learning: Untangling the evidence.
- [3] Major, L., Francis, G. A., & Tsapali, M. (2021). The effectiveness of technology-supported personalised learning in low-and middle-income countries: A metaanalysis. *British Journal of Educational Technology*, 52(5), 1935-1964.
- [4] Akyuz, Y. (2020). Effects of intelligent tutoring systems (ITS) on personalized learning (PL). *Creative Education*, 11(06), 953.
- [5] Shemshack, A., & Spector, J. M. (2020). *A systematic literature review of personalized learning terms*.
- [6] El-Sabagh, H. A. (2021). *Adaptive e-learning environment based on learning styles and its impact on development students' engagement*. *Education and Information Technologies*, 18, Article 53.
- [7] Pelánek, R., Effenberger, T., & Jarušek, P. (2024). *Personalized recommendations for learning activities in online environments: A modular rulebased approach*. *Education and Information Technologies*, 34, 1399–1430.
- [8] Liu, Z., & Wang, Z. (2025). *The impact of emotional design on multimedia learning outcomes: The moderating role of task difficulty*. *Behavioral Sciences*, 15(3), 397.

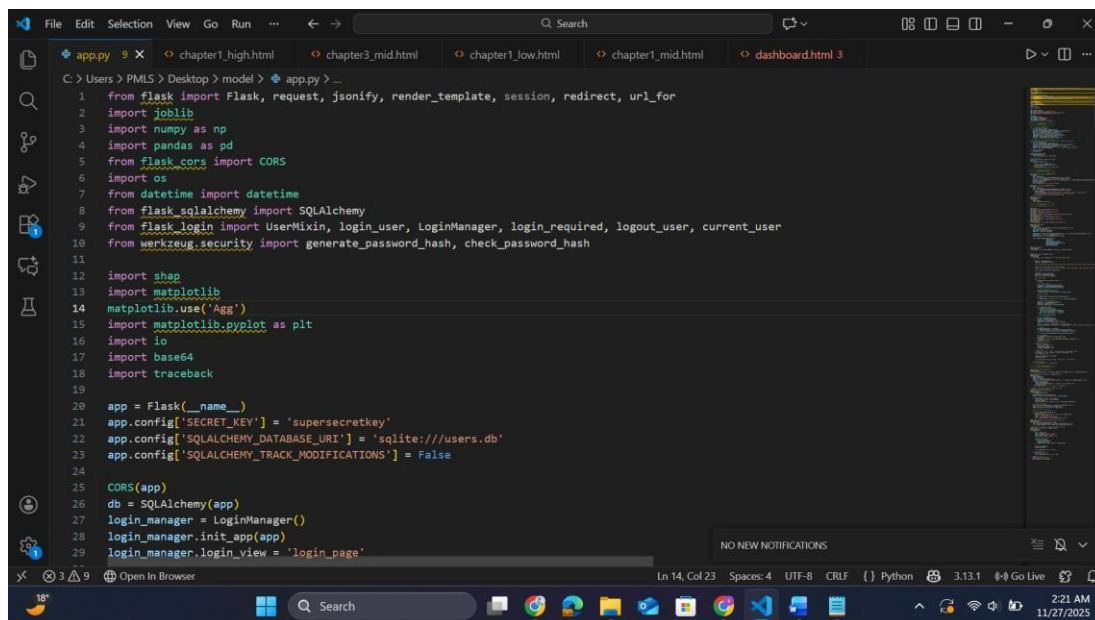
- [9] Shingjergji, K., Iren, D., Urlings, C., & Klemke, R. (2025). *Design principles for affective online learning*. (Original research; open access).
- [10] Castillo-Avila, S. et al. (2023). *Towards an affective tutoring system with multimedia content adaptation*. CEUR Workshop Proceedings.
- [11] Al-Qora'n, A. et al. (2025). *Designing inclusive and adaptive content in Moodle*. MDPI.
- [12] Ayeni, O. O., Al Hamad, N. M., Chisom, O. N., Osawaru, B., & Adewusi, O. E. (2024). *AI in education: A review of personalized learning and educational technology*.
- [13] Hashim, S., Omar, M. K., Ab Jalil, H., & Sharef, N. M. (2022). *Trends on technologies and artificial intelligence in education for personalized learning: Systematic literature review*.
- [14] Liu, M., & Yu, D. (2022, December 12). *Towards intelligent e-learning systems*.
- [15] Murtaza, M., Ahmed, Y., Shamsi, J. A., Sherwani, F., & Usman, M. (2022). *AI-based personalized e-learning systems: Issues, challenges, and solutions*. IEEE.
- [16] Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P. (2022). *Adaptive learning using artificial intelligence in e-learning: A literature review*.
- [17] Kabudi, T., Pappas, I., & Olsen, D. H. (2021). *AI-enabled adaptive learning systems: A systematic mapping of the literature*.
- [18] Kashive, N., Powale, L., & Kashive, K. (2023). *Understanding user perception toward artificial intelligence (AI)-enabled e-learning*.

- [19] Saleh, S. S., Nat, M., & Aqel, M. (2021). *Sustainable adoption of e-learning from the TAM perspective*.
- [20] Halkiopoulou, C., & Gkintoni, E. (2023). *Leveraging AI in e-learning: Personalized learning and adaptive assessment through cognitive neuropsychology—A systematic analysis*.
- [21] Ellikkal, A., & Rajamohan, S. (2023). *AI-enabled personalized learning: Empowering management students for improving engagement and academic performance*.
- [22] Maier, U., & Klotz, C. (2021). *Personalized feedback in digital learning environments: Classification framework and literature review*.
- [23] Karthika, R., Jesi, V. E., Christo, M. S., Deborah, L. J., Sivaraman, A., & Kumar, S. (2023). *Intelligent personalised learning system based on emotions in e-learning*.
- [24] Essa, S. G., Celik, T., & Human-Hendricks, N. E. (2023). *Personalized adaptive learning technologies based on machine learning techniques to identify learning styles: A systematic literature review*. IEEE.
- [25] Shakya Khanal, S., Prasad, P. W. C., Alsadoon, A., & Maag, A. (2019, December 14). *A systematic review: Machine learning-based recommendation systems for elearning*.
- [26] Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2021). *Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education*.

- [27] Alamri, H. A., Watson, S., & Watson, W. (2020). *Learning technology models that support personalization*
- [28] Salloum, S. A., Alomari, K. M., Alfaisal, A. M., Aljanada, R. A., & Basiouni, A. (2025). Emotion recognition for enhanced learning: using AI to detect students' emotions and adjust teaching methods. *Smart Learning Environments*, 12(1), 21.
- [29] Alsubai, S. (2022). Emotion detection using deep normalized attention-based neural network and modified-random forest. *Sensors*, 23(1), 225.

## APPENDICES

### APPENDIX A: Libraries



```
1 from flask import Flask, request, jsonify, render_template, session, redirect, url_for
2 import joblib
3 import numpy as np
4 import pandas as pd
5 from flask_cors import CORS
6 import os
7 from datetime import datetime
8 from flask_sqlalchemy import SQLAlchemy
9 from flask_login import UserMixin, login_user, LoginManager, login_required, logout_user, current_user
10 from werkzeug.security import generate_password_hash, check_password_hash
11
12 import shap
13 import matplotlib
14 matplotlib.use('Agg')
15 import matplotlib.pyplot as plt
16 import io
17 import base64
18 import traceback
19
20 app = Flask(__name__)
21 app.config['SECRET_KEY'] = 'supersecretkey'
22 app.config['SQLALCHEMY_DATABASE_URI'] = 'sqlite:///users.db'
23 app.config['SQLALCHEMY_TRACK_MODIFICATIONS'] = False
24
25 CORS(app)
26 db = SQLAlchemy(app)
27 login_manager = LoginManager()
28 login_manager.init_app(app)
29 login_manager.login_view = 'login_page'
```

### APPENDIX B: Database

```

File Edit Selection View Go Run ... Search
app.py 9 X chapter1_high.html chapter3_mid.html chapter1_low.html chapter1_mid.html dashboard.html 3
C:\Users> PMLS\Desktop> model> app.py ...
26 db = SQLAlchemy(app)
27 login_manager = LoginManager()
28 login_manager.init_app(app)
29 login_manager.login_view = 'login_page'
30
31
32 class User(UserMixin, db.Model):
33     id = db.Column(db.Integer, primary_key=True)
34     username = db.Column(db.String(150), unique=True, nullable=False)
35     password = db.Column(db.String(150), nullable=False)
36     name = db.Column(db.String(150), nullable=False)
37     saved_level = db.Column(db.String(50), nullable=True)
38     completed_chapters = db.Column(db.String(50), default="")
39     shap_plot = db.Column(db.Text, nullable=True)
40     shap_text = db.Column(db.String(500), nullable=True)
41
42
43 class BehaviorLog(db.Model):
44     id = db.Column(db.Integer, primary_key=True)
45     user_id = db.Column(db.Integer, db.ForeignKey('user.id'), nullable=False)
46     timestamp = db.Column(db.DateTime, default=datetime.utcnow)
47     trigger_reason = db.Column(db.String(50))
48     details = db.Column(db.String(200))
49
50 with app.app_context():
51     db.create_all()
52
53 @login_manager.user_loader
54 def load_user(user_id):

```

## APPENDIX C: Authentication

```

File Edit Selection View Go Run ... Search
app.py 9 X chapter1_high.html chapter3_mid.html chapter1_low.html chapter1_mid.html dashboard.html 3
C:\Users> PMLS\Desktop> model> app.py ...
67
68 @app.route('/auth/signup', methods=['POST'])
69 def signup():
70     data = request.json
71     user = User.query.filter_by(username=data.get('username')).first()
72     if user: return jsonify({"error": "User already exists"}), 400
73     new_user = User(username=data.get('username'), name=data.get('name'), password=generate_password_hash(data.get('password')), method='pbk
74     db.session.add(new_user)
75     db.session.commit()
76     return jsonify({"message": "Account created!"})
77
78 @app.route('/auth/login', methods=['POST'])
79 def login():
80     data = request.json
81     user = User.query.filter_by(username=data.get('username')).first()
82     if user and check_password_hash(user.password, data.get('password')):
83         login_user(user)
84         if user.saved_level: return jsonify({"redirect": "/dashboard", "status": "existing_user"})
85         else: return jsonify({"redirect": "/survey", "status": "new_user"})
86     return jsonify({"error": "Invalid credentials"}), 401
87
88 @app.route('/logout')
89 @login_required
90 def logout():
91     logout_user()
92     return redirect(url_for('home'))
93
94 # =====
95 PAGE ROUTES

```

## APPENDIX D: Routes

```

95
96 @app.route('/')
97 def home(): return render_template('index.html')
98 @app.route('/about')
99 def about(): return render_template('about.html')
100 @app.route('/features')
101 def features(): return render_template('SentellectPlatformFeatures.html')
102 @app.route('/login')
103 def login_page(): return render_template('login.html')
104 @app.route('/signup')
105 def signup_page(): return render_template('signup.html')
106 @app.route('/survey')
107 @login_required
108 def survey_page(): return render_template('questionnaire.html')
109
110 @app.route('/dashboard')
111 @login_required
112 def dashboard():
113     level = current_user.saved_level if current_user.saved_level else 'mid'
114     label = level.capitalize()
115     shap_image = current_user.shap_plot
116     shap_text = current_user.shap_text
117
118     completed_list = current_user.completed_chapters.split(',') if current_user.completed_chapters else []
119     completed_list = [x for x in completed_list if x]
120     progress_percent = int((len(completed_list) / 6) * 100)
121
122     return render_template('dashboard.html',
123                           level=level,

```

## APPENDIX E: Model Inputs

```

133
134
135
136 @app.route('/predict', methods=['POST'])
137 @login_required
138 def predict():
139     if not model: return jsonify({"error": "Model not loaded"}), 500
140
141     try:
142         req_data = request.get_json()
143         features = req_data.get("features")
144
145         cols = ['Q3A', 'Q5A', 'Q18A', 'Q13A', 'Q16A', 'Q17A', 'Q21A', 'Q24A', 'Q26A', 'Q31A', 'Q34A', 'Q37A', 'Q38A', 'Q42A', 'Q2A', 'Q4A', 'Q7A', 'Q9A', 'Q1
146
147         q_map = {"Q3A": "Positive Feeling", "Q5A": "Initiative", "Q18A": "Future Hope", "Q13A": "Sadness", "Q16A": "Interest", "Q17A": "Self Wort
148
149         df = pd.DataFrame([features], columns=cols)
150
151
152         prediction = model.predict(df)[0]
153         pred_str = str(prediction).strip()
154         print(f"Model Prediction: {pred_str}")
155
156
157     try:
158         print("Attempting SHAP (Pipeline Mode)...")
159         plt.clf()
160
161

```

## APPENDIX F: SHAP Pipeline

```

138 def predict():
158     try:
159         print("Attempting SHAP (Pipeline Mode)...")
160         plt.clf()
161
162
163         step_names = list(model.named_steps.keys())
164         preprocessor = model.named_steps[step_names[0]]
165         classifier = model.named_steps[step_names[-1]]
166
167
168         X_trans = preprocessor.transform(df)
169         if hasattr(X_trans, "toarray"): X_trans = X_trans.toarray()
170
171
172         try:
173             feature_names = preprocessor.get_feature_names_out()
174         except:
175             feature_names = [f"Feature {i}" for i in range(X_trans.shape[1])]
176
177         explainer = shap.TreeExplainer(classifier)
178         shap_values = explainer(X_trans)
179         shap_values.feature_names = list(feature_names)
180
181
182         if len(shap_values.shape) == 3:
183             classes = classifier.classes_
184             class_idx = list(classes).index(pred_str)
185             vals = shap_values.values[0, :, class_idx]

```

## APPENDIX G: SHAP Graph

```

199     # --- PLOT ---
200     plt.figure(figsize=(10, 6), dpi=100)
201     if hasattr(shap_values, 'shape') and len(shap_values.shape) > 1:
202         shap.plots.waterfall(shap_values[0], max_display=10, show=False)
203     else:
204         shap.plots.waterfall(shap_values, max_display=10, show=False)
205
206     buf = io.BytesIO()
207     plt.savefig(buf, format="png", bbox_inches='tight')
208     buf.seek(0)
209     current_user.shap_plot = base64.b64encode(buf.getvalue()).decode('utf-8')
210     plt.close()
211     print("🟢 SHAP SUCCESS")
212
213
214     except Exception as e:
215         print(f"⚠️ SHAP ERROR: {e}")
216         traceback.print_exc()
217         current_user.shap_plot = None
218         current_user.shap_text = None
219
220     # 3. Save Level
221     if pred_str in ['High', 'Severe', 'Extremely Severe']: user_level = "high"
222     elif pred_str in ['Mid', 'Moderate', 'Medium']: user_level = "mid"
223     else: user_level = "low"
224
225     current_user.saved_level = user_level
226     db.session.commit()

```

## APPENDIX H: Behavioural logs

```

File Edit Selection View Go Run ... Search
app.py x chapter1_high.html chapter3_mid.html chapter1_low.html chapter1_mid.html dashboard.html 3
C:\Users\PMLS\Desktop>model>app.py>predict
285
286 # [NEW] Route to Log Adaptive Behavior (Frontend -> Database)
287 @app.route('/api/log_behavior', methods=['POST'])
288 @login_required
289 def log_behavior():
290     try:
291         data = request.json
292         reason = data.get('reason', 'unknown')
293         mood = data.get('mood', 'neutral')
294         rage_clicks = data.get('rageClicks', 0)
295
296         # Create a new log entry
297         new_log = BehaviorLog(
298             user_id=current_user.id,
299             trigger_reason=reason,
300             details=f"Mood: {mood}, RageClicks: {rage_clicks}"
301         )
302
303         db.session.add(new_log)
304         db.session.commit()
305
306         return jsonify({"status": "success"})
307
308     except Exception as e:
309         print(f"Log Error: {e}")
310         return jsonify({"status": "error"}), 500
311
312 if __name__ == '__main__':
313     print("Starting Flask Server...")
NO NEW NOTIFICATIONS
Ln 181, Col 9 Spaces: 4 UTF-8 CRLF Python 3.13.1 Go Live

```

## APPENDIX I: Chatbot.py

```

templates > chatbot.html > html
2 <html lang="en">
358
359 <body>
360 <header>
361 <div class="navbar">
362 <a href="{{ url_for('dashboard') }}" class="logo">
363 <div class="logo-icon"></div>
364 <span>Sentellect</span>
365 </a>
366 <div class="nav-buttons">
367 <a href="{{ url_for('dashboard') }}" class="nav-btn">
368 <i class="fas fa-home"></i> Dashboard
369 </a>
370 <a href="{{ url_for('profile') }}" class="nav-btn">
371 <i class="fas fa-user"></i> Profile
372 </a>
373 <a href="{{ url_for('logout') }}" class="nav-btn logout">
374 <i class="fas fa-sign-out-alt"></i> Logout
375 </a>
376 </div>
377 </div>
378 </header>
379
380 <div class="chat-container">
381 <div class="chat-header">
382 <h1><img alt="Gemini AI logo" data-bbox="300 680 315 690"/> Gemini AI Chatbot</h1>
383 <p>Experience a sleek, modern chat interface with AI-powered conversations</p>
384 </div>
385

```

## APPENDIX J: Dashboard

```

templates > <> dashboard.html > html > head > style > body
1 <!DOCTYPE html>
2 <html lang="en">
3 <head>
4   <meta charset="UTF-8">
5   <meta name="viewport" content="width=device-width, initial-scale=1.0">
6   <title>Dashboard - Sentellect</title>
7   <link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/6.4.0/css/all.min.
8   <style>
9     :root {
10      --primary: #1e40af;
11      --bg: #f8fafc;
12      --white: #ffffff;
13      --text: #1e293b;
14      --success: #10b981;
15      --card-shadow: 0 10px 25px rgba(0,0,0,0.05);
16    }
17
18    * {
19      margin: 0;
20      padding: 0;
21      box-sizing: border-box;
22    }
23
24    body {
25      font-family: 'Segoe UI', Tahoma, Geneva, Verdana, sans-serif;
26      background-color: var(--bg);
27      color: var(--text);
28      display: flex;
29      flex-direction: column;

```

## APPENDIX K: App.py

```

<> dashboard.html 3 • app.py 9+ X
app.py > ...
1 from flask import Flask, request, jsonify, render_template, session, redirect, url_for
2 import joblib
3 import numpy as np
4 import pandas as pd
5 from flask_cors import CORS
6 import os
7 from flask_sqlalchemy import SQLAlchemy
8 from flask_login import UserMixin, login_user, LoginManager, login_required, logout_user, current_user
9 from werkzeug.security import generate_password_hash, check_password_hash
10
11 # --- Graphing Libraries ---
12 import shap
13 import matplotlib
14 matplotlib.use('Agg') # Prevent GUI errors
15 import matplotlib.pyplot as plt
16 import io
17 import base64
18 import traceback
19
20 app = Flask(__name__)
21 app.config['SECRET_KEY'] = 'supersecretkey'
22 app.config['SQLALCHEMY_DATABASE_URI'] = 'sqlite:///users.db'
23 app.config['SQLALCHEMY_TRACK_MODIFICATIONS'] = False
24
25 CORS(app)
26 db = SQLAlchemy(app)
27 login_manager = LoginManager()
28 login_manager.init_app(app)
29 login_manager.login_view = 'login page'

```

## APPENDIX L: Chatbot Interface



# Gemini AI Chatbot

Experience a sleek, modern chat interface with AI-powered conversations

hi

Hi there! How can I help you today?

write the derivate formulas in short form

Here are the most common derivative formulas in short form (using the notation  $\frac{d}{dx} f(x) = f'(x)$ ):

- Function  $f(x)$  | Derivative  $f'(x)$  | Description
- $c$  (constant) |  $0$  | Constant Rule
- Power Rule ( $f(x) = x^n$ ) |  $nx^{n-1}$  | Power Rule
- $e^x$  |  $e^x$  | Exponential Rule (Base  $e$ )
- $a^x$  |  $a^x \ln(a)$  | Exponential Rule (Base  $a$ )
- $\ln(x)$  |  $\frac{1}{x}$  | Logarithmic Rule (Natural Log)
- $\log_a(x)$  |  $\frac{1}{x \ln(a)}$  | Logarithmic Rule (Base  $a$ )
- $c \cdot f(x)$  |  $c \cdot f'(x)$  | Constant Multiple Rule
- $f(x) \pm g(x)$  |  $f'(x) \pm g'(x)$  | Sum/Difference Rule
- $f(x) \cdot g(x)$  |  $f'(x)g(x) + f(x)g'(x)$  | Product Rule
- $\frac{f(x)}{g(x)}$  |  $\frac{f'(x)g(x) - f(x)g'(x)}{g(x)^2}$  | Quotient Rule
- $f(g(x))$  |  $f'(g(x)) \cdot g'(x)$  | Chain Rule
- $\sin(x)$  |  $\cos(x)$  |  $\cos(x)$  |  $-\sin(x)$  |  $\tan(x)$  |  $\sec^2(x)$  |  $-\csc^2(x)$  |  $\cot(x)$  |  $-\csc^2(x)$  |  $\arctan(x)$  |  $\frac{1}{1+x^2}$

Type your message here...

Send

Clear Chat

← Back to Dashboard

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