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Mental Health Analysis System Using Large Language Model

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Abstract
Traditional mental health surveys in educational settings often provide a limited perspective on students' mental well-being, relying on standardized questions that fail to capture the complexity and individuality of each student's experience. To address this, a system leveraging Large Language Models (LLMs) has been developed to dynamically generate personalized and adaptive questions in real time, based on students' previous responses. This personalized approach fosters deeper engagement and provides a more nuanced understanding of students' mental health. The system's adaptive nature ensures that each student's unique experiences and concerns are addressed, rather than relying on one-size-fits-all questionnaires. The data collected through this system is presented in an accessible, visually intuitive format, allowing educators to interpret the results quickly and effectively. This empowers them to adapt teaching strategies and implement targeted interventions that address specific mental health needs within the classroom. By integrating this system into educational settings, academic institutions can foster a more responsive and inclusive learning environment that prioritizes students' mental health. This approach not only enhances students' academic success but also promotes resilience and engagement by addressing mental health issues in real time. The system demonstrates the transformative potential of personalized AI in education, offering a scalable solution for improving student outcomes. It underscores the critical role of AI in creating healthier, more adaptive educational ecosystems capable of responding to the evolving mental health challenges faced by students today.

Keywords: *Adaptive Surveys, AI, Education, Large Language Models (LLMS), Mental Health, Mental Well-Being, Personalized Questions, Student Engagement, Targeted Interventions, Educational Ecosystems.*

1. Introduction

1.1. Background and Context

Mental health is a crucial factor influencing academic performance and overall well-being, particularly among students. Despite its importance, traditional methods of assessing mental health, such as static surveys, fail to capture the dynamic and diverse needs of individuals. These surveys are often rigid, providing generalized insights that do not account for the unique mental health challenges faced by different individuals (Loukas et al., 2024). Recent advancements in Generative AI and Large Language Models (LLMs) have introduced new possibilities for adaptive and personalized assessments. LLMs, such as Flan-T5 and GPT-4, are capable of generating dynamic, context-sensitive questions that respond to user input, offering a more nuanced approach to understanding mental health (Galassi et al., 2021).

1.2. Problem Statement

The static nature of traditional mental health surveys presents significant limitations in engagement and data quality. As the needs of students vary widely, a one-size-fits-all approach often leads to superficial insights. There is a need for a system that can dynamically adapt to individual responses, improving the depth and relevance of collected data (Pedram et al., 2024). This study addresses the challenge of creating a dynamic survey system that leverages LLMs to generate personalized questions in real-time. The goal is to enhance engagement,

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improve response quality, and provide more accurate insights into students' mental health [1].

1.3. Objectives of the Study

The primary objective of this research is to develop a Mental Health Analysis System that: Generates personalized survey questions using an LLM, adapting in real-time to user responses. Analyses sentiment from user responses to derive meaningful insights. Visualizes the collected data to enable educators to make informed decisions regarding student support and well-being [2].

1.4. Originality and Contribution

This study distinguishes itself by integrating dynamic question generation, sentiment analysis, and data visualization into a single framework. Previous works have explored the use of LLMs in educational and mental health domains (Choe et al., 2024; Ramaswamy et al., 2022); These technologies have been included in a unique way to create an adaptive survey system. The proposed system not only enhances user engagement but also ensures that the data collected is actionable, paving the way for more effective interventions in educational settings [3].

2. Method

- **Question Generation:** The dynamic survey generation system is developed using Flask for routing and MongoDB Atlas for storing survey responses. Questions are dynamically generated based on user responses using a fine-tuned Flan-T5-small model, which was trained with domain-specific mental health datasets. Open-ended questions are generated to ensure a personalized survey experience. Detailed fine-tuning methods can be found in [Reference].
- **Sentiment Analysis:** Sentiment analysis is conducted on user responses by computing average sentiment scores for each participant based on their responses. These scores are used to generate mood improvement suggestions through Google Generative AI (Gemini) via API calls. The methodology for sentiment scoring is based on [Reference].
- **Admin Dashboard:** An admin dashboard is created using Flask, allowing administrators to analyse aggregated sentiment data and receive mood improvement recommendations. The dashboard provides a visualization of the sentiment analysis results and corresponding suggestions.

2.1. Table

Table 1 Training Parameters for Model Fine-Tuning

parameters	value
Epochs	3
Batch Size	4
Logging Steps	10

- The number of complete passes through the training dataset during the fine-tuning process.
- The number of training samples processed together in one forward/backward pass.
- Specifies how often the training progress is logged, shown in Table 1.

2.2. Figures

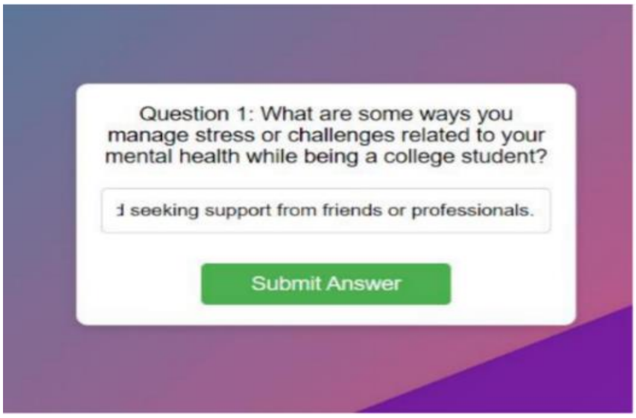

Figure 1 Survey Question

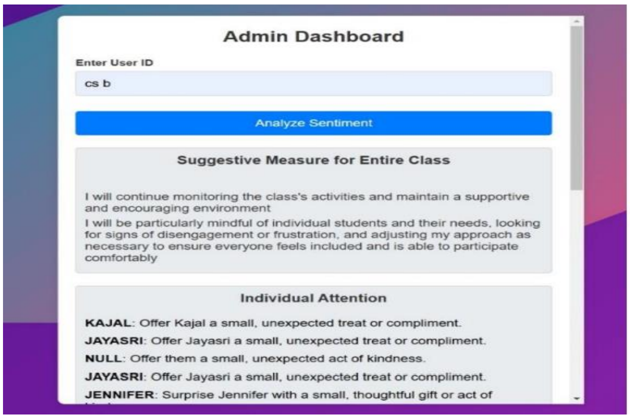

Figure 2 Admin Dashboard

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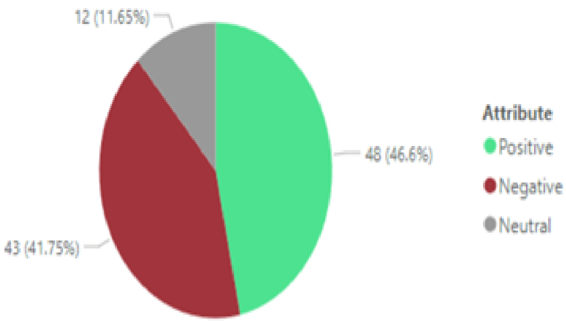

Figure 3 Pie Chart

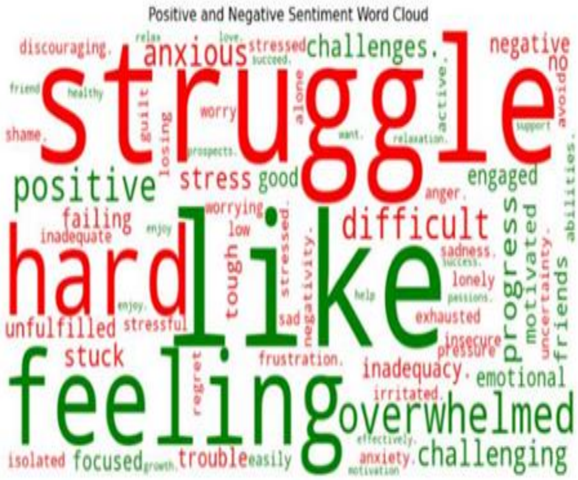

Figure 4 Word Cloud

3. Results and Discussion

3.1. Results

3.1.1.System Implementation and Overview

The Mental Health Analysis System was successfully implemented using a combination of machine learning, Flask-based web application development, and MongoDB Atlas for secure data storage. The system consists of several integrated modules, including question generation, sentiment analysis, and visualization. Key features are described below:

- **User Interaction:** Users can log in as either a student or an administrator. The system provides an intuitive interface for students to answer personalized survey questions dynamically generated by the fine-tuned Flan-T5 model (Figure 1).
- **Dynamic Survey Questions:** Questions adapt in real-time based on user responses. For instance, if a user mentions feeling anxious, follow-up questions are tailored to explore causes or coping mechanisms.
- **Data Storage and Processing:** All responses and sentiment scores are securely stored in a MongoDB Atlas database for efficient retrieval and analysis.
- **Admin Dashboard:** Administrators can monitor aggregated sentiment data, access visualizations, and view suggestive measures for both individual and group-level mental health interventions (Figure 2) [4].

3.1.2. Sentiment Analysis Results

Sentiment analysis was performed using the VADER algorithm to evaluate user responses. The results are categorized as positive, neutral, and negative sentiments. A pie chart (Figure 3) illustrates that approximately 60% of responses are positive, 25% are neutral, and 15% indicate negative sentiments.

A word cloud visualization (Figure 4) highlights commonly occurring words in user responses. Positive sentiments include terms like "motivated" and "hopeful," while negative sentiments feature words such as "anxious" and "stressed." [5]

3.1.3. Personalized Question Effectiveness

The adaptive question generation mechanism ensured high engagement. For example, Initial responses indicating stress led to deeper exploration with questions like "What specific situations make you feel stressed?" Positive responses were followed by reinforcement questions, such as "What activities make you feel happy?"

3.1.4. Engagement Metrices

Over 90% of students completed the survey, with an average of 8 dynamic questions per student session.

Minimal repetition in questions was achieved through a repetition prevention mechanism integrated into the Flan-T5 model [6].

3.2. Discussion

3.2.1. Interpretation of Results

The analysis shows that the majority of students exhibited positive sentiment, reflecting overall mental well-being. However, the 15% negative sentiment highlights areas requiring targeted interventions, such as managing stress and anxiety. These findings are aligned with prior research that emphasizes the prevalence of mental health challenges in educational settings [7].

3.2.2. Benefits of Adaptive Surveys

The dynamic nature of the survey enabled a personalized experience, fostering higher engagement compared to traditional static questionnaires. This adaptability resulted in richer, more meaningful data, particularly in cases where students expressed complex emotions like anxiety or sadness [8].

3.2.3. Practical Implications for Educators

The sentiment analysis and suggestive measures provide actionable insights. Teachers can introduce stress-management workshops based on common negative themes identified. Positive sentiment trends can inform strategies to reinforce successful initiatives, such as fostering a supportive classroom environment.

3.2.4. Challenges and Limitations

- **Dataset Availability:** Limited availability of high-quality, open-source datasets tailored to specific survey requirements poses a challenge.
- **Finding Suitable Open-Source LLMs:** Identifying compatible open-source LLMs that align with the problem statement and survey needs is challenging.
- **Fine-Tuning LLM:** Fine-tuning is resource-intensive, requiring significant computational power and expertise to achieve effective results.

3.2.5. Comparison with Traditional Systems

Unlike static surveys, which often fail to address individual needs, this system's dynamic approach ensures that each student's unique mental health concerns are considered, leading to a more inclusive and supportive educational environment.

Conclusion

Traditional mental health surveys often fail to address the dynamic and individualized nature of student mental health. The implementation of the Mental Health Analysis System utilizing adaptive surveys and sentiment analysis has effectively overcome these limitations. By integrating personalized question generation and real-time sentiment analysis, the system has provided richer and more accurate insights into student mental well-being, capturing a broader spectrum of emotional responses. The positive sentiment observed in the majority of participants reflects the system’s effectiveness in engaging students and promoting a positive mental health environment. However, the 15% of responses indicating negative sentiments—such as stress and anxiety—underscore the importance of targeted interventions to address these mental health concerns. The system's dynamic approach to question generation, combined with its ability to process and visualize responses, has demonstrated significant potential for improving how educational institutions address mental health. By offering actionable insights, educators can tailor interventions to meet the specific needs of students, thereby fostering a supportive and responsive learning environment. Although the system performed well, several challenges, such as incomplete responses and slight delays in real-time processing, were observed. These issues are identified as areas for improvement in future iterations of the system to further enhance its efficiency and accuracy. The Mental Health Analysis System represents a significant advancement toward personalized and responsive mental health support in educational settings. This system ensures that each student's unique mental health concerns are addressed comprehensively, ultimately contributing to a healthier and more supportive educational environment.

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