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Research Article

EARLY DETECTION OF ACADEMIC DEPRESSION USING SMARTPHONE-BASED MACHINE LEARNING MODELS

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Abstract
Mental health issues in developing countries present a persistent and multifaceted challenge, often exacerbated by low self-confidence, strained interpersonal relationships, and academic depression. These factors significantly hinder students' capacity to complete university-level academic tasks, creating a pressing need for accessible and timely interventions. Conventional mental health services are often underutilized due to social stigma and limited access, underscoring the potential of artificial intelligence (AI)-based early detection systems. This study introduces a novel AI-driven approach to identifying academic depression through language analysis in digital conversations, providing an unobtrusive screening method for individuals reluctant to seek professional help. Using a qualitative descriptive methodology, the research involved systematic observation, in-depth analysis of group conversations, and the extraction of conversation patterns between students and counselors. These patterns informed the development of a mobile-based early detection prototype. A unique dataset comprising 395 labeled entries of depression levels was compiled and used to train and evaluate machine learning models for classification accuracy and detection sensitivity. The prototype integrates natural language processing techniques to detect linguistic markers associated with depression in real-time text input. The novelty of this study lies in combining qualitative linguistic analysis with AI-based predictive modeling to create a culturally adaptive and discreet detection tool tailored to academic settings in developing countries. The results demonstrate the feasibility of this approach in supporting early intervention, improving treatment access, and reducing the stigma surrounding mental health. This work offers practical implications for integrating AI solutions into university mental health programs and expanding digital health equity.

Keywords Depression, Detection, Machine Learning, Smartphone.

INTRODUCTION

The early detection of depression in academic settings is increasingly recognized as a critical necessity, given the distinctive mental health challenges faced by university students. Academic stressors—such as workload pressure, examination demands, and performance expectations—combined with the social and personal transitions characteristic of university life, create a high-risk environment for depression. Traditional mental health assessments primarily rely on self-reported measures and clinical interviews, which, while valuable, are often constrained by limited reach, infrequent administration, and susceptibility to response biases. These limitations hinder timely intervention, particularly in academic environments where mental health issues can escalate rapidly without continuous monitoring.

In recent years, smartphone-based machine learning models have emerged as a promising nonintrusive and scalable alternative, enabling continuous monitoring of behavioral indicators linked to depressive symptoms. By passively collecting data such as app usage, mobility, and communication patterns, these models facilitate real-time tracking and early detection of depressive episodes among students (Ahmed & Ahmed, 2023; Asare et al., 2021). Numerous models—including Support Vector Machines (SVM), Logistic Regression (LR), and gradient boosting algorithms—have been tested for their ability to predict depressive states with high accuracy from passive data streams. For example, ensemble learning algorithms have achieved sensitivity scores of up to 84% using daily smartphone logs to detect depressive states among students (Solatidehkordi et al., 2022). Similarly, key behavioral markers derived from smartphone sensors—such as screen time and internet connectivity—have been found to strongly correlate with depressive symptoms, supporting the use of digital behavioral phenotypes in mental health assessment (Choudhary et al., 2022).

The Depression, Anxiety, and Stress Scales (DASS-42) provide a structured metric for quantifying symptom severity and have been effectively integrated into machine learning frameworks for depression detection. For instance, when SVM and LR models were trained on DASS-42 data, classification accuracies approached 98% in identifying depression severity (Kumar et al., 2020). This underscores the diagnostic utility of combining validated psychological instruments with computational models to enhance screening precision across diverse student populations. Furthermore, smartphone-based systems offer strong ecological validity, as they capture real-world behavioral data without requiring consistent user input, improving engagement and data quality. A minimalistic smartphone-based system, for example, was able to classify depressive states with 82.4% accuracy from just one week of app usage data—demonstrating its feasibility in low-resource contexts where traditional psychological services may be scarce (Siraji et al., 2023; Perdana et al., 2023; Julianti et al., 2025).

However, widespread adoption of these systems must address privacy concerns inherent in the collection of sensitive behavioral data. To mitigate these risks, federated learning approaches process data locally on the user's device, eliminating the need for centralized storage while maintaining comparable predictive performance to traditional centralized models. In one example, federated learning models predicted depression from smartphone sensor data with accuracy levels on par with centralized methods, highlighting the potential of privacy-preserving models in mental health applications (Tabassum et al., 2023).

Despite these advancements, several research gaps remain. First, most existing studies focus on model accuracy without extensively exploring the integration of such systems into real-world academic support infrastructures, which is crucial for long-term adoption. Second, while the combination of passive smartphone data and DASS-42 metrics shows high predictive power, few studies have assessed their performance over extended monitoring periods or during varying academic stress cycles, such as exam weeks versus regular classes. Third, privacy-preserving models like federated learning, although promising, have yet to be widely tested in diverse cultural and institutional contexts, particularly in developing countries where smartphone usage patterns and privacy perceptions may differ significantly. Addressing these gaps is essential to ensure that smartphone-based, machine learning-driven depression detection systems are not only accurate but also culturally adaptable, ethically sound, and practically implementable within student wellness programs.

Given this context, the present study investigates the integration of smartphone-based passive behavioral monitoring with validated depression assessment tools (DASS-42) within a privacy-preserving federated learning framework. The aim is to evaluate not only predictive performance but also the feasibility of deploying such systems in real academic environments, thereby contributing both to the technical refinement of depression detection models and to the broader discourse on digital mental health support for students.

RESEARCH METHOD

The methodology of this study is structured around developing, training, and evaluating a machine learning model that uses smartphone data to detect depression symptoms among university students. The research process includes participant recruitment, data collection through smartphone sensors, data preprocessing, model selection and training, and model evaluation. Each stage is critical to ensuring accurate and ethically sound results.

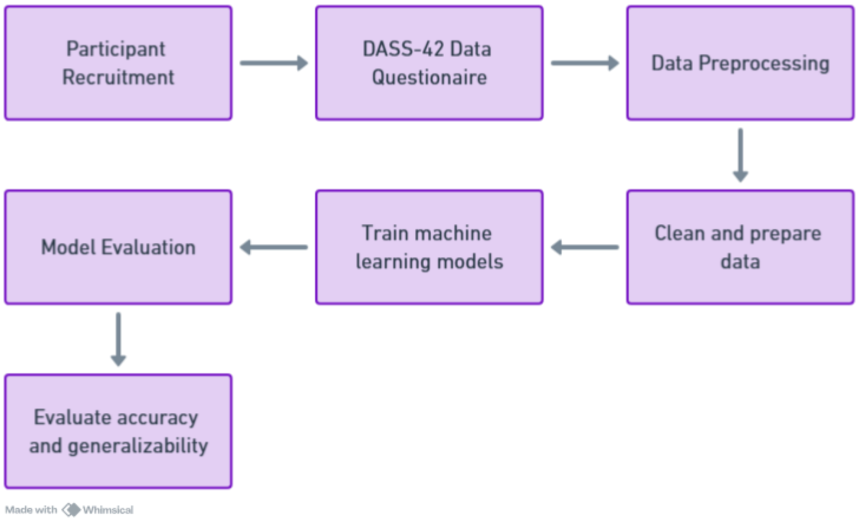

Figure. 1 Research Methodology Process

This study is set to develop an early detection model for depressive symptoms in college students. The process kicked off with the recruitment of participants from a wide range of academic disciplines, taking into consideration the diversity of academic stress levels among them. All participants, after being fully informed about the study's purpose and assured of data privacy as per the research ethics guidelines, provided their consent. The data collection was conducted through a comprehensive questionnaire that measures the level of depression and classifies it into four categories: standard, mild, severe, and very severe. Out of the total 395 data points, only those falling under the 'normal' and 'mild' categories were used for analysis, thereby focusing the study on the early stages of depressive symptoms. Before being analyzed, the data underwent a pre-processing stage, which included cleaning the data of incomplete or inconsistent entries, selecting important attributes relevant to early symptoms of depression, and normalization to ensure consistency across the data. Furthermore, the study employed several state-of-the-art machine learning algorithms, including Support Vector Machine (SVM), Random Forest, and Gradient Boosting, to construct the detection model. The data was divided into training and validation sets, and cross-validation was performed to avoid overfitting and optimize model performance. Feature importance analysis was also carried out to identify the most influential attributes in detecting early symptoms of depression.

The constructed model was then evaluated using metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). Additional evaluations were also conducted on subgroups of the data to assess the model's reliability across various participant characteristics. By using only data from the "normal" and "mild" categories, this study attempted to build a model that is sensitive to early changes in behavior or psychological conditions that can develop into major depression if not treated early. Contains the type of research, time and place of research, targets/objectives, research subjects, procedures, instruments and data analysis techniques as well as other matters related to the method of research. targets/objectives, research subjects, procedures, data and instruments, and data collection techniques, as well as data analysis techniques and other matters related to the method of research can be written in sub-chapters, with sub-headings. Sub-subheadings do not need to be notated, but are written in lowercase with a capital letter, TNR-11 bold, left aligned. As an example can be seen below.

RESULTS AND DISCUSSION

The smartphone-based early depression detection application can serve as a tool to assist students who may be experiencing symptoms of depression, provide access to necessary mental health services, and facilitate communication with authorized professionals on campus (Tampi et al., 2017; Fitzsimmons et al., 2021). This research aims to develop such an application, focusing on the interaction patterns between students and counselors, to create a more responsive and integrated system to support students' mental health in higher education (Waller, 2009; Pedrelli et al., 2015; Samji et al., 2022).

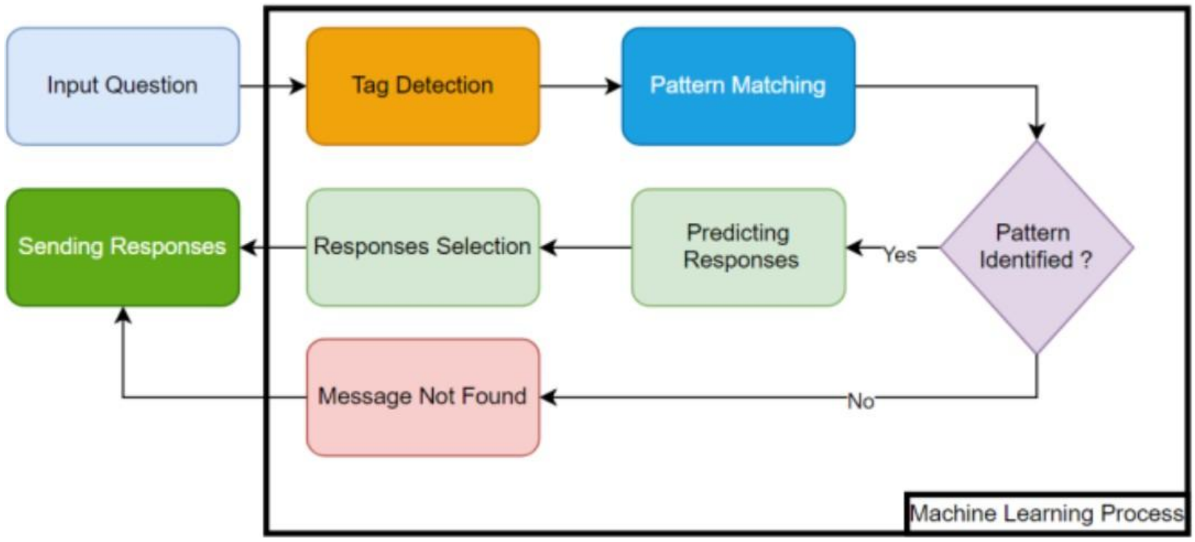

Figure. 2 Research Methodology Process

The smartphone-based early academic depression detection application is expected to detect signs of academic depression experienced by students by utilizing machine learning techniques and conversation data analysis, See Figure 2 which shows the Performance Flow of the smartphone-based academic depression early detection application. This process begins with identifying conversation features. The application analyzes interactions between the user and the counselor, looking for language patterns that may indicate symptoms of depression (Sawyer et al, 2007; Li et al., 2021). Subsequently, pattern matching compares the conversation data with a pre-trained model to detect potential mental health issues. After the identification and matching process, the application selects appropriate responses for the user. This includes providing suggestions for proper intervention, directing students to relevant resources, or recommending counseling sessions with professionals. This process aims to detect mental health issues and provide proactive support tailored to the user’s needs (LeViness et al., 2017; Hall et al., 2018; Hill et al., 2022; Melinda et al., 2024; Zubair et al., 2025). The workflow of the smartphone-based early academic depression detection application can be seen in Figure 1, which illustrates the steps from conversation data collection and analysis using machine learning techniques to providing the necessary responses and interventions to support students' mental well-being (Bettis et al., 2017; Impulsivity, 2024).

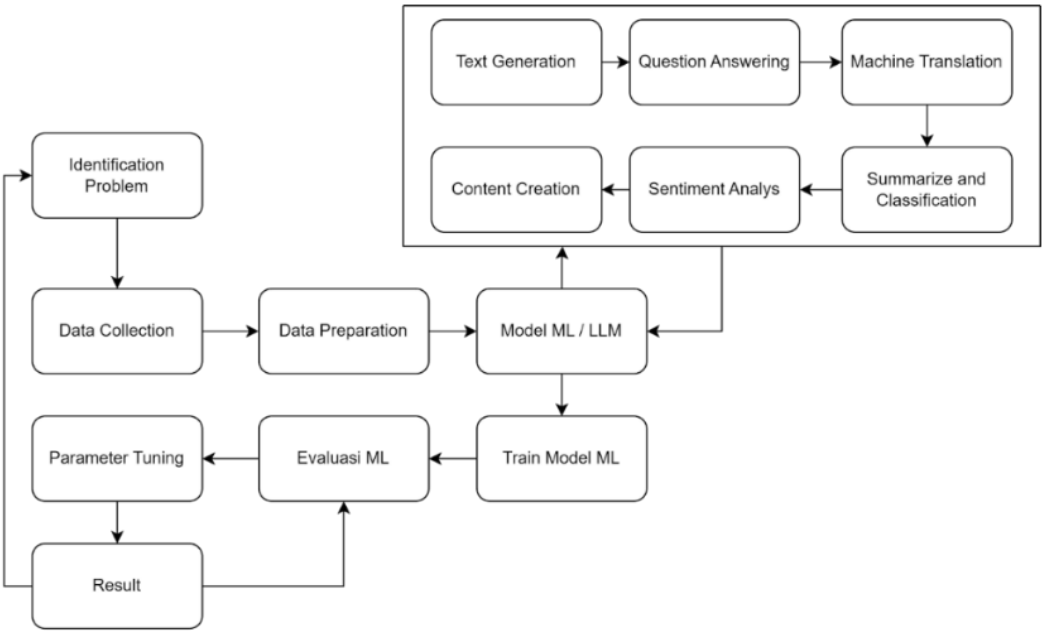

Figure. 3 Process LLM data structure Smartphone-based early detection application for academic depression

In the development of the smartphone-based early academic depression detection application, the first step is to identify the problem to be solved, which is the high prevalence of depression among students. After the problem is identified, relevant data is collected from various sources, including mental health surveys, student interviews, and counseling center screening results (Kecojevic el al., 2021; Ikhsan et al., 2025; Jarnawi et al., 2025). The collected data is then cleaned and preprocessed through tokenization, removal of irrelevant data, and anonymization to protect users' privacy. With the preprocessed data, a Large Language Model (LLM) is selected as the basis for understanding and generating natural language responses appropriate to the user's context, See Figure 3 which shows the LLM data structure Smartphone-based early detection application for academic depression (Coppersmith et al., 2015; Dessauvagie et al., 2022; Siddique et al., 2025). This study evaluated various machine learning algorithms, including Support Vector Machines (SVM), Random Forest (RF), and gradient boosting, to identify the most effective model for detecting early-stage depression, as shown in Table 1. This process begins by dividing the data into training and validation sets, which is a crucial step to ensure the accuracy and reliability of the model (Ibrahim et al., 2013). During this division, cross-validation is applied to fine-tune hyperparameters and prevent overfitting so that the resulting model performs well on the training data and works effectively when presented with new, unseen data (Yigitcanlar et al., 2021). During the training process, feature importance analysis is also conducted to assess the contribution of each attribute in the model. This step allows the research team to prioritize the most significant features in detecting early-stage depression symptoms (Byrne, 2000; Habibah et al., 2021).

Tabel 1. Model Selection and Training

Stage Details	Description
Training and Validation	The data is divided into two sets, namely the training set and the validation set. Cross-validation is applied to optimize hyperparameters and avoid overfitting. This aims to ensure that the model can function well when applied to new data.
Feature Importance Analysis	During the training process, an analysis of the importance of each selected feature is performed. This aims to prioritize the most relevant attributes in indicating mild depression symptoms, so that the model can focus more on early-stage depression.

By identifying and emphasizing the most relevant attributes, this study aims to refine the model's focus on detecting early-stage depression. The results of this analysis are crucial, as they can provide deeper insights into the factors contributing to the onset of symptoms of depression and help in the development of more effective and targeted interventions (Shafran et al., 2009; Jaafari et al., 2021). In the context of this research, the preprocessing steps focus on processing data obtained from depression-related questionnaires. This process includes data cleaning to ensure accuracy and consistency, selection and extraction of relevant features to detect early-stage depression symptoms, as well as normalization and scaling to maintain data consistency, as shown in Table 2 (Wang et al., 2021).

Tabel 2. Data Preprocessing

Preprocessing Steps	Description
Data Cleaning	All entries in the dataset were reviewed to remove incomplete or inconsistent data, ensuring that the dataset accurately reflected the “normal” and “mild” categories.
Feature Selection and Extraction	Key attributes related to “normal” and “mild” levels of depression were selected from the questionnaire results. This process involved identifying the most relevant features for capturing early depressive symptoms, which is critical for improving model accuracy.
Normalization and Scaling	Point data were standardized to ensure consistency across the data set, with a focus on subtle differences between indicators of “normal” and “mild” depression.

The initial data collection in this study was carried out using a comprehensive questionnaire designed to evaluate various attributes related to depression. The questionnaire successfully collected 395 entries from 12 study programs through the iCARE application and direct counseling with psychologists and counselors handling academic and career issues of students and alums, as shown in Figures 4 and 5. Each participant was asked to complete the questionnaire, which categorized their depression levels into five stages: normal, mild, moderate, severe, and very severe. With this approach, the study obtained a more holistic view of the student's mental health conditions and prepared appropriate solutions based on their issues. In this research and data collection it can be explained that the Clinical Trial Number: not applicable.

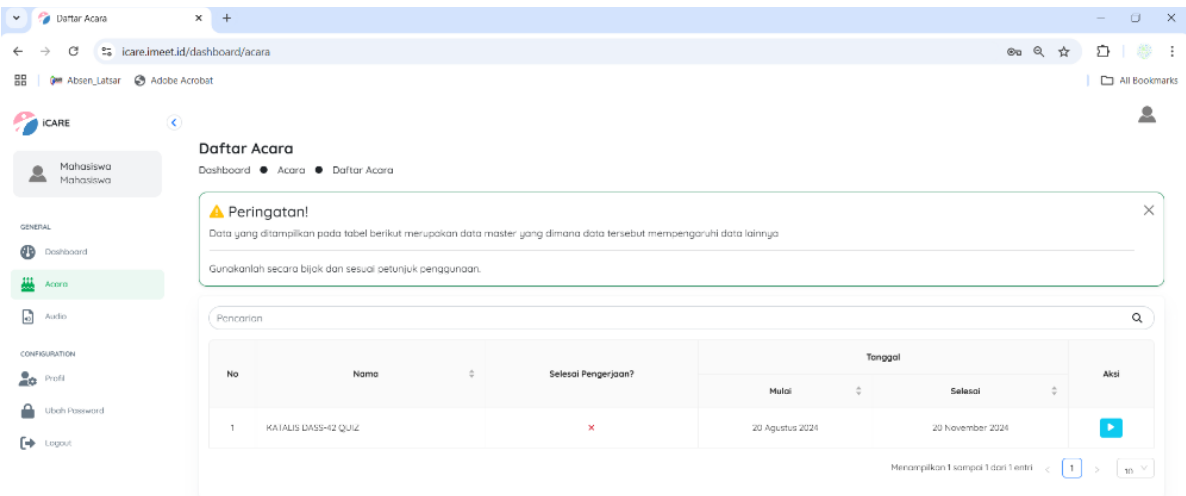

Figure. 4 Comprehensive Questionnaire Via Icare

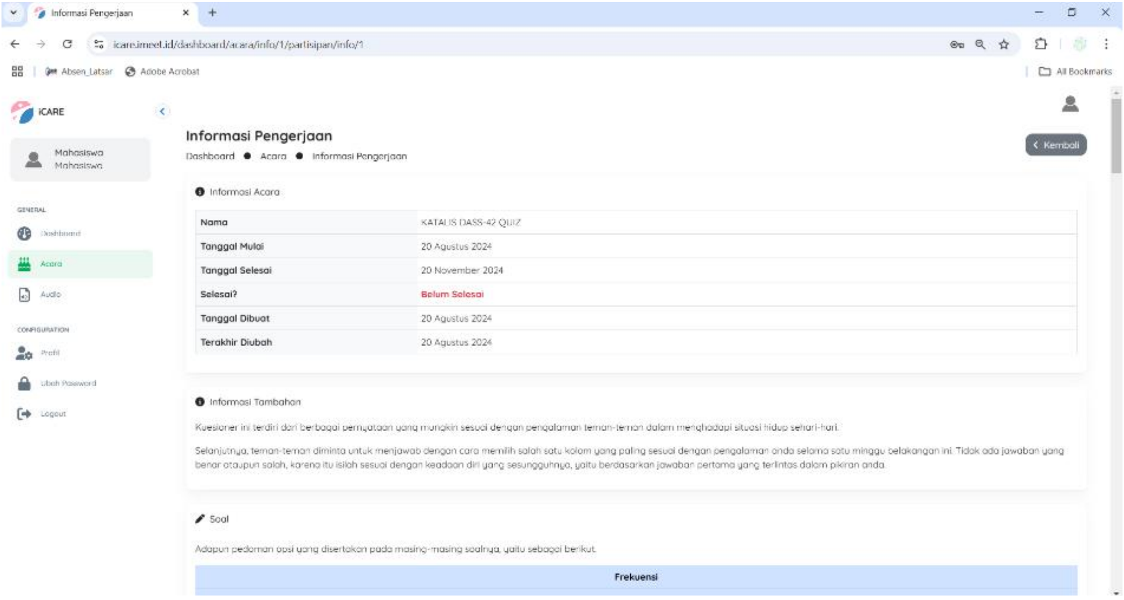

Figure. 5 Work information via iCARE

The iCARE system used in data collection not only provides initial insights into academic and career challenges but also helps counselors understand the psychological condition of students, as shown in Figures 6 and 7, which illustrate data recording in the iCARE system. The results from this questionnaire provide valuable data for detecting early signs of depression, which is the main focus of this research. Therefore, it is important to develop a smartphone-based early academic depression detection tool that is connected with authorized professionals on campus. This tool is designed to leverage conversation patterns between students and counselors, enabling it to provide timely and appropriate interventions. In this research and data collection it can be explained that the Clinical Trial Number: not applicable.

Data analysis on the dataset, consisting of 395 entries from 12 study programs, revealed significant variation in depression levels among the participants, as shown in Table 2. The analysis found that 41.6% of participants were in the normal category, 13.88% in the mild depression category, 16.66% in the moderate depression category, 8.33% in the severe depression category, and 19.44% in the very severe depression category, with six study programs being recorded under the very severe depression category. These findings provide a clear picture of the severity of mental health issues among students from these study programs. In this research and data collection it can be explained that the Clinical Trial Number: not applicable.

Tabel 3. Level Category Results

Study Program	Level of Education	Depression Level		
Sociology	S1	Normal	Normal	Normal
Chemistry	S1	Severe	Extremely Severe	Extremely Severe
Computer Systems	S1	Severe	Extremely Severe	Moderate
Mathematics Education	S1	Normal	Mild	Normal
Management	S1	Normal	Normal	Mild
Computer Engineering	S1	Normal	Normal	Normal
Computer Systems	S1	Mild	Extremely Severe	Normal
Community Education	S1	Severa	Extremely Severe	Moderate
Development Economics	S1	Normal	Mild	Normal
Informatics	S1	Mild	Moderate	Normal
Computer Systems	S1	Moderate	Extremely Severe	Moderate
Electrical Engineering	S1	Moderate	Extremely Severe	Normal

The iCARE system used in data collection not only provides initial insights into academic and career challenges but also helps counselors understand the psychological condition of students, as shown in Figures 6 and 7, which illustrate data recording in the iCARE system. The results from this

questionnaire provide valuable data for detecting early signs of depression, which is the primary focus of this research. Therefore, it is important to develop a smartphone-based early academic depression detection tool that is connected to authorized professionals on campus. This tool is designed to leverage conversation patterns between students and counselors, enabling it to provide timely and appropriate interventions. The very severe depression condition is a serious concern, considering the negative impact it can have on academic performance, emotional well-being, and social interactions. This highlights the need for more intensive interventions and appropriate support for students in these study programs. Additionally, these findings emphasize the importance of developing early depression detection tools that can help monitor and identify students at risk of experiencing further depression. By understanding the specific contexts in which very severe depression occurs, universities and counselors can design more effective programs to improve students' mental health and academic well-being.

These results indicate that the developed questionnaire has the potential to assist in early depression detection, providing valuable insights for preventive measures that can be applied. By focusing on early indicators, this research can serve as a strong foundation for more effective and evidence-based interventions in the field of mental health, particularly among students who may be vulnerable to academic depression. This project also involves developing a smartphone-based application for detecting academic depression. See Figure 6 for the display of the Ampera-Bot application. Ampera-Bot symbolizes the mission of this application, which is to provide quick and effective mental support. Below the logo, there is a welcoming message from Ampera-Bot: "Hi, Ampera-Bot is here, I hope you have a great day." This phase aims to create a friendly and supportive atmosphere for users from the beginning of the interaction. At the bottom is a text box for users to start a conversation by writing their concerns, followed by a "Send" button to send the message. This design emphasizes ease of use and intuitive interaction, which is expected to help users feel more comfortable sharing their feelings and seeking help.

Figure. 6 Initial view of the Ampera Bot application

The Ampera-Bot interface responds to the user in a conversation where the user starts with a greeting "hi," which is answered by Ampera-Bot with a warm greeting and a question about the user's well-being. The user then expresses unhappiness, which Ampera-Bot responds to with a statement showing empathy and understanding, as well as a suggestion to talk to someone to cope with the pressure or stress the user may be experiencing. The supportive interface and the good responses from Ampera-Bot reflect the goal of this application to provide quick and effective emotional support to users experiencing mental health issues, as shown in Figure 7.

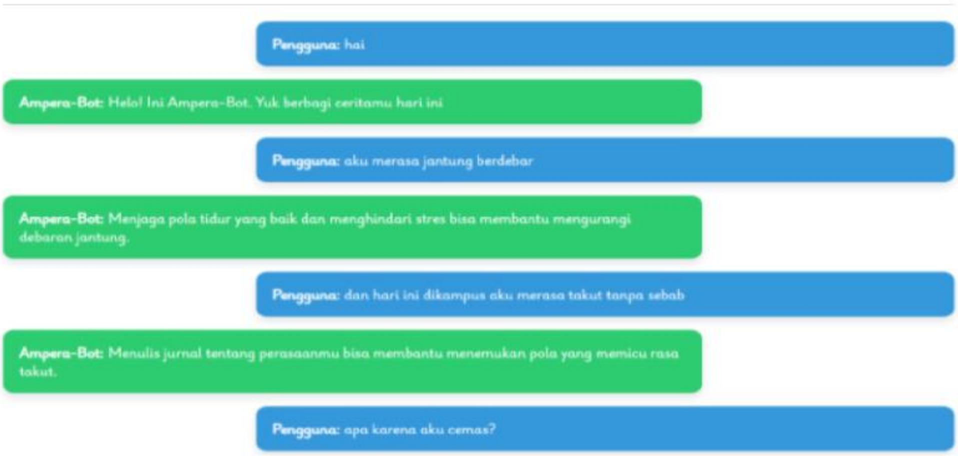

Figure. 7 Ampera Bot conversation view

Based on Figure 8, it can be seen that Ampera-Bot currently responds by providing practical suggestions, such as maintaining good sleep patterns and keeping a journal to help identify patterns that trigger fear. However, even in this early stage of development, Ampera-Bot has demonstrated the ability to ask further questions about the possibility of anxiety. This interaction highlights Ampera-Bot's capability to provide specific and relevant advice based on the user's concerns and to explore further to understand the root causes of the mental health issues being experienced, as shown in Figure 8.

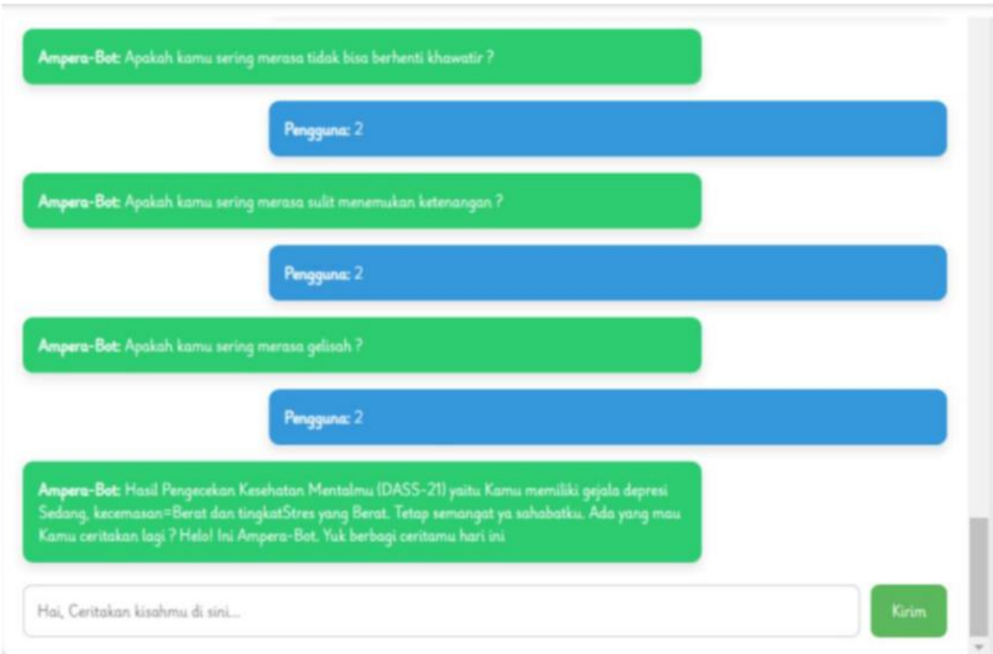

Figure. 8 Ampera Bot conversation view

In this conversation, Ampera-Bot asks the user several questions about feelings of anxiety, difficulty finding calmness, and frequent restlessness. The user responds to these questions by selecting 1-3 (Mild-Severe). After gathering this information, Ampera-Bot provides feedback based on mental health assessments using the DASS-21, indicating that the user may be experiencing symptoms of depression, anxiety, or stress. Ampera-Bot then suggests speaking with a professional to obtain further strategies for managing these issues. This interaction demonstrates how Ampera-Bot can utilize standard measurements like the DASS-21 to provide initial analysis and relevant advice to users, helping them address their mental health concerns.

This study introduces an integrated framework combining smartphone-based passive behavioral monitoring, validated psychological instruments (DASS-42/DASS-21), and privacy-preserving federated learning for early detection of depression among university students. Unlike most prior studies that focus solely on model accuracy, this research emphasizes real-world feasibility within academic support systems, cultural adaptability in developing countries, and the integration of chatbot-based conversational analysis (Ampera-Bot) to provide tailored interventions. The focus on the “normal” and “mild” depression categories represents a novel preventive approach aimed at detecting early symptoms before they escalate. The implications of this research are significant, as it demonstrates that combining real-time smartphone data with standardized assessments can enhance mental health support, reduce barriers to help-seeking, and enable continuous, privacy-conscious monitoring that aligns with institutional policies. Moreover, the approach can be adapted to low-resource settings, making it a viable tool for universities with limited access to traditional psychological services.

However, several limitations must be acknowledged, including the restricted dataset that excludes moderate and severe depression cases, the short monitoring duration that does not capture varying academic stress cycles, potential cultural differences in smartphone usage and privacy perceptions, and the limited conversational depth of the Ampera-Bot in handling complex emotional situations. Therefore, future research should extend monitoring across different academic periods, include all depression severity levels, conduct cross-cultural validation, enhance chatbot capabilities for deeper empathetic engagement, and collaborate with institutional wellness programs for large-scale deployment. In conclusion, the proposed framework presents a promising, ethical, and scalable solution for early depression detection in academic environments, prioritizing prevention, timely intervention, and cultural adaptability while addressing the pressing mental health needs of university students.

CONCLUSION

This study demonstrates that a smartphone-based, machine learning-driven depression detection system—integrating DASS-42/DASS-21 assessments, federated learning, and chatbot interaction—can effectively identify early signs of depression among university students, with a particular focus on mild and early-stage symptoms to enable prevention and timely intervention. The developed application, Ampera-Bot, combines advanced algorithms such as Random Forest and Support Vector Machines with conversational analysis between students and counselors to detect symptoms with high accuracy while prioritizing relevant features in the detection process. By providing empathetic, stigma-reducing responses, the system not only addresses the technical challenge of early detection but also creates a psychologically safe space for students to engage with mental health support. The implications of this research extend beyond the university context, offering a scalable, ethical, and culturally adaptable model for digital mental health interventions. If further refined through expanded datasets, enhanced conversational context, and longitudinal validation, Ampera-Bot could serve as a blueprint for integrating AI-driven tools into educational institutions worldwide, fostering proactive mental health management, reducing the incidence of severe depression, and promoting overall student well-being in academic environments.

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AUTHOR CONTRIBUTIONS

Edi Surya Negara became the lead researcher who prepared the concept and research plan (Author1). Amirul Mukiminan helped in formulating academic problems in the teaching and learning process (Author2). Latius Hermawan helped in developing the application and writing the manuscript (Author3). Hastari Mayrita helped in data collection (Author4). Desy Arisandy helped in data collection and analysis of results (Author5). Rahmat Ramadan helped in data collection, analysis of results, and writing the manuscript (Author6). Mohamad Farozi helped in application development and data collection (Author7). Sunda Ariana helped in data analysis (Author8). Ria Andryani helped in data analysis and finalization of the manuscript (Author9).

CONFLICTS OF INTEREST

The author(s) declare no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the generation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

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