AI-DASA: AI-Based Depression, Anxiety, and Stress Assessment

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ABSTRACT

This article presents the design, implementation, and validation of AI-DASA, an innovative web-based predictive system designed to detect emotional disorders, specifically anxiety, depression, and stress, in university students at an early stage. AI-DASA is based on advanced Natural Language Processing (NLP) techniques and utilizes large-scale language models to analyze free-text documents written by students. The system was evaluated in a three-week experiment involving expert psychologists and 200 university students who interacted with the platform. Validation was conducted at three levels: operational efficiency compared to the traditional process, usability from the perspective of mental health experts, and overall satisfaction perception among students. The results show that AI-DASA achieved an average accuracy of 94% in detecting disorders, significantly reducing the evaluation time from 48 hours to just 20 minutes per case and eliminating the need for direct human intervention in the initial diagnostic phase. Both experts and students reported high levels of satisfaction and usability. This system represents a promising tool for emotional screening in educational settings, particularly in environments with limited access to mental health professionals, thus contributing to the earlier and more efficient detection of emotional problems in the student population.

Keywords-depression; anxiety; stress; emotional disorders; Natural Language Processing (NLP)

I. INTRODUCTION

Mental health has become a key focus in global public health initiatives over the past few years. The World Health Organization estimates that one in eight people worldwide lives with a mental disorder, with young people being one of the most vulnerable groups [1]. This situation has worsened due to the COVID-19 pandemic, which has significantly increased anxiety, depression, and stress levels in the general population [2]. In Latin America, the impact of mental health issues is particularly evident among student communities. For example, in Peru, local studies indicate that more than 30% of university students in cities such as Lima and Huánuco have experienced symptoms associated with mental disorders [3]. According to data from the Ministry of Health, there was a 20% increase in mental health cases attended to in 2022 [4]. This highlights an urgent need to strengthen prevention efforts and provide specialized care. In addition, the early detection of symptoms like anxiety, depression, and stress among university students poses challenges, particularly due to the limited use of reliable predictive systems in educational environments [5]. In a context characterized by significant academic, personal, and socioeconomic demands, this limitation obstructs timely intervention, which directly affects students' emotional well-being and academic performance [6].

Researchers have proposed solutions that use Artificial Intelligence (AI) and Natural Language Processing (NLP) to assess users' emotional states based on their digital interactions. Machine Learning (ML) models used for text analysis on social media platforms, such as Twitter and Reddit, have achieved high accuracy levels in detecting symptoms of depression and anxiety [7]. Advanced models, such as MindLiFt [8], incorporate multimodal techniques—such as facial analysis, NLP, and chatbots—to monitor students' emotional states in real-time and provide personalized recommendations through cognitive-behavioral therapy. In [9], a stacking ensemble model on responses from the PHQ-9 questionnaire achieved an accuracy of 94.69% in detecting depression among engineering university students. Despite these advances, most studies encounter methodological limitations, such as small sample sizes, imbalanced data, or a focus on only one type of variable, decreasing their generalizability [10]. In addition, increased emphasis is necessary on data ethics, algorithmic bias, and standardizing models intended for clinical use [11].

In [12], a mobile application was developed to detect depression in university students. This approach integrated NLP and ML models, involved extracting linguistic features from users' written responses, and used classifiers, such as Random Forest (RF) and Support Vector Machine (SVM), achieving accuracy rates greater than 90%. Additionally, the system provided automated recommendations for users, enhancing its usability in educational settings. In [13], a medical application employed Gradient Boosting (GB) along with techniques such as Word2Vec and N-Gram to identify textual patterns linked to anxiety, depression, and stress. This model achieved an accuracy of 84.2%, demonstrating its effectiveness for use on mobile platforms, particularly in predictive applications. In clinical settings, a dynamic NLP-based model was introduced in [14] to assess the risk of psychosis in patients, demonstrating significant enhancements over static models. This method is suitable for mobile environments requiring continuous monitoring.

Studies such as [15] highlight that automated analysis of children's drawings using computer vision and DL constitutes a promising alternative to detect psychological and mental health problems, significantly reducing the complexity and time required in traditional methods based on manual interpretation by specialists, while NLP also demonstrates great scope to address these problems from the perspective of textual and emotional analysis. In [16], federated learning was employed to predict depression in more than 500,000 high school students in China, attaining an Area under the Curve (AUC) score of 0.9123. This method demonstrated the potential to integrate NLP with federated learning, enabling the development of mobile applications that protect user privacy. Another example is NamuBot, a conversational agent that provides emotional support [17], detects signs of distress through the user's language and offers therapeutic responses aimed at helping decision-making and providing psychological assistance.

In [18], a conversational chatbot, powered by ChatGPT 4.0, was specifically designed to support Korean youth, receiving positive feedback for its empathetic tone and cultural sensitivity. However, some limitations were identified, especially regarding its level of personalization. Models such as GPT-3.5 and GPT-4 can effectively identify depressive symptoms, achieving accuracy up to 90.2% by analyzing spontaneous digital journal entries [19]. This highlights the potential for integrating these chatbots into automated dialogue systems designed to support emotional well-being. In [20], the effectiveness of chatbots like Woebot and Wysa was emphasized, as they provide strategies based on Cognitive Behavioral Therapy (CBT) and AI for emotional monitoring. These systems were successfully integrated into mobile applications to reduce the stigma surrounding therapy and enhance access to early interventions. In [21], the effectiveness of conversational systems using sentiment analysis was examined, concluding that automatic emotion detection enables real-time interventions for students at high emotional risk. In [22], a specialized corpus was developed in the Bengali language to train chatbots to assess the severity of depression. This study utilized both traditional algorithms and neural networks, including LSTM and GRU, demonstrating the effectiveness of multilingual chatbots trained for specific cultural contexts. In [23], a review of the use of AI in social media for predicting mental disorders was presented, noting that real-time interactive chatbots could be integrated into social platforms to address urgent mental health issues, provided that ethical and privacy principles are respected.

The primary contributions of this study are as follows:

- Presents a conceptual model for the development of AI-DASA. The goal is to design a web-based predictive system that integrates NLP and ML to analyze students' written responses to open-ended questionnaires. The system aims to generate personalized emotional profiles and effectively identify linguistic patterns linked to emotional classification, enhancing transparency within the system and assisting professionals in making clinical decisions.
- Integrates explainability criteria into the predictive model, facilitating the visualization of results through reports and alerts targeted at mental health professionals.
- Conducts a systematic review of current technological proposals that utilize NLP and AI in educational settings to detect emotional symptoms. The review analyzes various approaches, outcomes, and limitations, helping to contextualize and justify the importance of the AI-DASA system within the existing landscape.

This study develops a culturally contextualized, AI-assisted assessment tool, specifically designed for university students in Latin America. Unlike traditional methods based on closed-ended questionnaires, AI-DASA uniquely integrates NLP through GPT-4 mini and prompt engineering to analyze open-text responses. This combination provides an innovative, resource-efficient approach for detecting early emotional risks in academic environments with limited infrastructure.

In the context of Peru, the studies in [9, 24] represent significant advances in the application of NLP for mental health. In [9], a predictive model applied stacking techniques to responses to the PHQ-9 questionnaire, achieving an impressive accuracy of 94.69% in detecting depressive symptoms. In [24], a comparative study of NLP-based methods to detect mental disorders among university students was presented. However, none of these studies proposed a comprehensive web-based system to identify symptoms of anxiety, depression, and stress in university populations using NLP, open-ended questionnaires, and automated analysis.

II. METHOD

This study used a methodological strategy to develop and implement a web-based predictive system called AI-DASA, designed to facilitate the early detection of anxiety, depression, and stress symptoms in university students. The method was practical, technology-oriented, and divided into three main phases: conceptual design, technical implementation, and functional validation. This structured approach facilitated a clear progression from developing the logical model to practical evaluation of the proposed system. In addition, it incorporated the principles of accessibility, explainability, and cultural adaptability.

AI-DASA takes a different approach compared to other proposals that rely on standardized closed-ended questionnaires. Instead, it uses NLP techniques to perform semantic analysis of spontaneous texts. This allows for the interpretation of subjective responses expressed in natural language by the students. In addition, it enables the automated generation of personalized recommendations and emotional profiles.

This section outlines the methodological decisions that guided the system's construction, including the design rationale, technical architecture, functional modules, and the validation process used to assess the system's effectiveness and user perception. Decisions were made based on various criteria, including functional integrity, technological feasibility, and academic rigor. In addition, observations collected during the project's midterm review were integrated, which enhanced both the predictive approach and methods to ensure the ethical use of sensitive data.

A. AI-DASA Model

The initial phase involved developing a conceptual model that aimed to define the primary functional components and illustrate how they interact based on the user flow that students would follow within the platform. This model was developed using a user-centered approach that followed the principles of experience-oriented design and preventive psychological intervention. Figure 1 demonstrates the conceptual design through a flow diagram, showing the key interactions between students and the system. Each open-ended response was processed using pre-defined GPT-4 mini prompts that were iteratively refined during a pilot phase. Prompts were crafted to elicit binary outputs (presence/absence of depression, anxiety, or stress) and associated keywords. In preprocessing, basic cleaning (tokenization, normalization, spelling correction), text normalization, token filtering, and anonymization were performed before submitting responses to the API to ensure optimal input quality.

AI-DASA utilizes GPT-4 mini via the OpenAI API in a zero-shot setting. The system does not involve fine-tuning; instead, it relies on carefully structured prompts—i.e., prompt engineering—to extract semantic patterns related to emotional states. This approach was chosen because of its adaptability, cost-efficiency, and ease of implementation in resource-limited university contexts. GPT-4 mini was used without model fine-tuning. Carefully crafted prompts were designed using prompt engineering to extract emotional indicators related to anxiety, depression, and stress. In addition, the system supports the automated generation of personalized feedback and emotional profiles. AI-DASA was designed to operate without direct human intervention, so this study focused on automating internal processes to maintain student confidentiality and ensure the system's scalability.

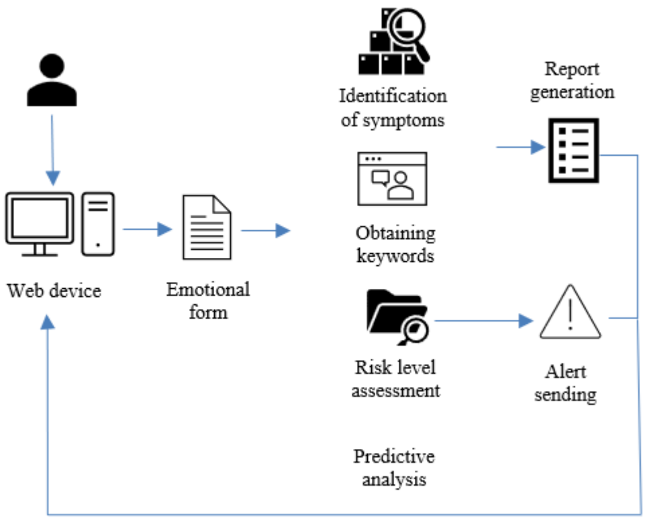


Fig. 1. AI-DASA web-system model.

The process begins when the student accesses the AI-DASA web system through a web browser. After the student fills out the open-ended text form, the backend processes the responses using the OpenAI API (ChatGPT-4 mini), which analyzes linguistic indicators associated with emotional states. Once the analysis is complete, a PDF report is generated that includes self-care recommendations. This entire process is ongoing, enabling prompt and independent assessments of the student's emotional well-being. Table I offers a brief explanation of each module that makes up the AI-DASA system.

TABLE I. AI-DASA MODULES

Modules	Description
Psychopathological Screening Form	This is based on DSM-5 criteria, enabling students to respond to open-ended questions about their mood, academic environment, and recent habits.
Predictive Analysis	Utilizes the ChatGPT API to process responses, employing NLP techniques to identify emotional symptoms.
Report Generation	Automatically generates a PDF file that includes the student's emotional profile, risk level, detected keywords, and personalized recommendations.
Alerts	An alert email is sent when a moderate or severe emotional risk level is detected.

AI-DASA differentiates itself from other systems by avoiding numerical scales or closed-ended questionnaires to assess risk levels. Instead, it utilizes NLP techniques to detect linguistic patterns linked to anxiety, depression, or stress. The emotional classification is derived from the content and structure of the student's writing, eliminating the need for a cumulative scoring system.

The emotional symptoms identified by the system are categorized into three types: anxiety, depression, and stress. These categories are determined by identifying keywords, emotional expressions, and specific grammatical structures, all of which are automatically extracted by the NLP model integrated with the OpenAI API. Table II presents examples of words commonly associated with each type of emotional symptom, which are recognized by AI-DASA during text analysis.

TABLE II. KEYWORDS ASSOCIATED WITH THE DETECTION OF MENTAL DISORDERS

Mental disorder	Keywords
Anxiety	Worry, nervous, agitated, fear, pressure, insecure, desperate, tension, can't concentrate, panic.
Depression	Sadness, emptiness, unmotivated, cry, tired, lack of motivation, alone, worthless, useless, dark, meaningless.
Stress	Exhausted, overwhelmed, collapsed, demand, too much, I can't take it anymore, pressured, overloaded, frustration.

Conversely, several studies on mental health suggest that access to educational and awareness-raising content positively impacts university students. Understanding self-care strategies, managing academic stress, and knowing how to seek professional support are essential for the emotional well-being of young people. However, excess or poorly organized information can lead to anxiety and confusion among those who are emotionally vulnerable.

B. AI-DASA Implementation

The second phase focused on the technical implementation of the AI-DASA system. This stage involved making decisions about the technological architecture, choosing development tools, configuring services, and building a modular web-based system. AI-DASA is a lightweight and scalable solution that can be deployed on low-cost servers without sacrificing performance, reinforcing its suitability in educational settings with limited infrastructure. The system is composed of a frontend, which serves as the user interface accessible via any browser, and a backend that handles logical processing, communication with external services, and storage of sensitive information. This structure effectively separates visual tasks from complex computational functions, thereby simplifying maintenance and updates.

The Flask microframework allowed us to build and scale the prototype rapidly while consuming minimal system resources. Unlike Django or FastAPI, Flask was selected for its lightweight structure, rapid prototyping capabilities, compatibility with modular API systems and NLP libraries, and flexibility in creating RESTful APIs. This API facilitates data flow between the web form, the semantic analysis engine (which utilizes the OpenAI API), and the PDF report generator. For data storage, SQLite was chosen due to its low resource consumption, portability, zero-configuration setup, suitability for deployment in university-scale applications, and ease of integration in medium-scale applications. This ensures data security and performance in pilot-scale scenarios. GPT-4 mini was selected for its high accuracy-to-cost ratio and acceptable performance in prompt-based emotion detection tasks.

AI-DASA adheres to privacy-by-design principles. Although GDPR does not apply legally in Peru, its principles were followed to protect sensitive student data. These include data minimization, anonymization, secure processing, and limited data retention. It was also clarified that the data is only temporarily stored and that student reports are automatically deleted after 24 hours, according to ethical and privacy standards.

1) Architecture

The AI-DASA system was designed using the client-server architecture, clearly separating the presentation, processing, and storage layers. The client layer (frontend) functions as a web interface accessible through modern browsers. The server (backend) is responsible for receiving responses from the emotional assessment form, processing them using NLP techniques, and generating personalized reports based on the results obtained (See Figure 2). The system was deployed on a Virtual Private Server (VPS) running Ubuntu 22.04 LTS on the DigitalOcean platform. This infrastructure provided complete control over the execution environment, allowing for the installation of necessary dependencies and the implementation of customized security settings. In addition, basic firewall rules were established, password encryption was implemented, and input sanitization was utilized to ensure the integrity of the processed data.

2) Development and Technologies Used

The technical development of AI-DASA was conducted in stages, emphasizing the implementation of minimum viable components to confirm the functionality of each module before its final integration. Open-source technologies and reliable libraries were used to ensure the system's robustness and its ability to adapt or expand in future versions. The frontend was designed as a responsive web interface, developed using HTML, CSS, and JavaScript. Its main purpose is to allow users to access an emotional assessment form, complete open-ended questions, and receive a generated report. The interface was tested by users to ensure clarity and ease of navigation. Additionally, basic principles of visual accessibility were incorporated.

The backend serves as the logical core of the system and integrates several key processes: (a) receiving and validating responses from the form, (b) preparing personalized prompts tailored to each type of emotional disorder, (c) sending requests to the OpenAI API using the ChatGPT GPT-4 mini model, (d) processing the model's response, which includes emotional labels, keywords, and recommendations, and (e) automatically generating a final PDF report using WeasyPrint, a library that converts dynamic HTML templates into styled documents.

3) Functional Modules

The AI-DASA system consists of a main authentication component and four modules, which work together as a series of autonomous but integrated processes. Each module has a specific function within the system, and its interactions follow the flow outlined in the conceptual design. The modules that were implemented are as follows.

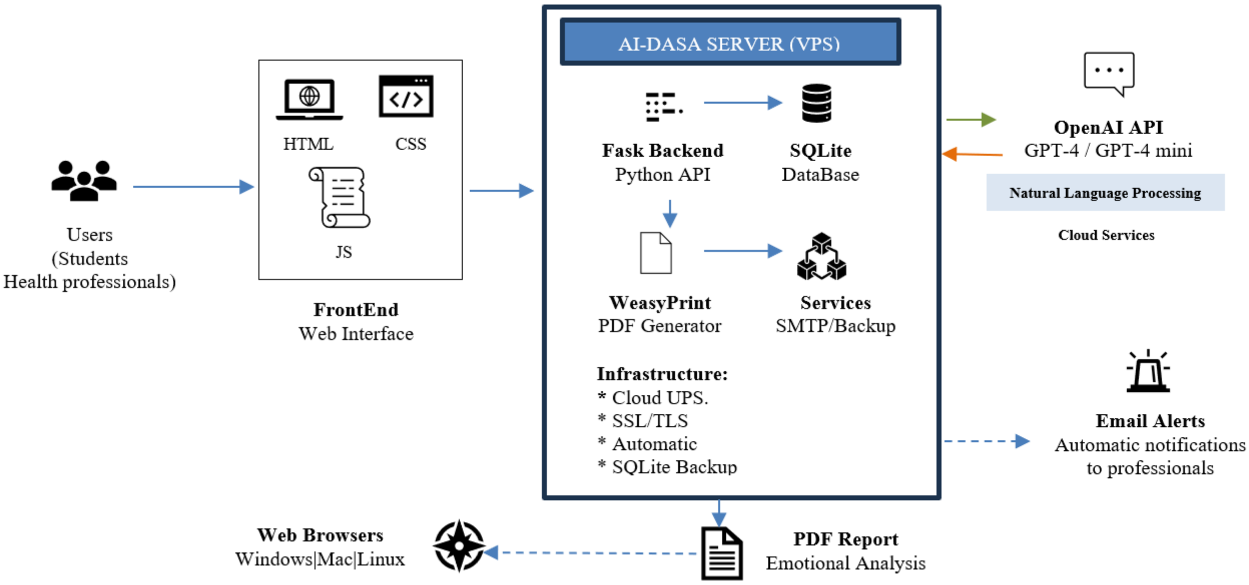
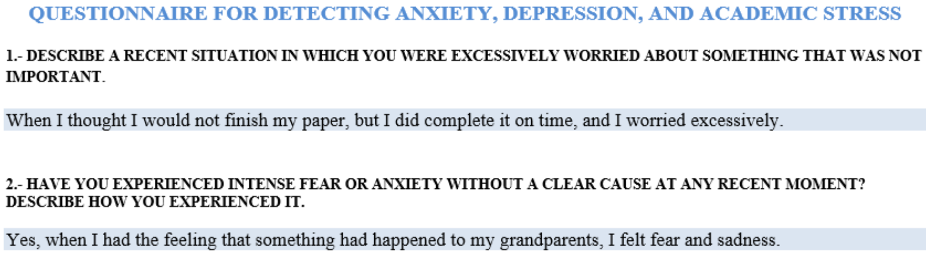


Fig. 2. Physical architecture of the AI-DASA predictive web system.



QUESTIONNAIRE FOR DETECTING ANXIETY, DEPRESSION, AND ACADEMIC STRESS

1.- DESCRIBE A RECENT SITUATION IN WHICH YOU WERE EXCESSIVELY WORRIED ABOUT SOMETHING THAT WAS NOT IMPORTANT.

When I thought I would not finish my paper, but I did complete it on time, and I worried excessively.

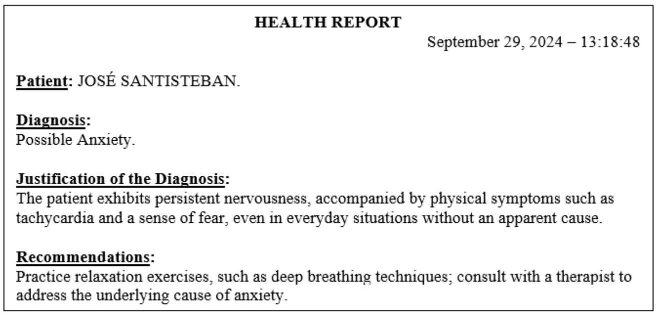
2.- HAVE YOU EXPERIENCED INTENSE FEAR OR ANXIETY WITHOUT A CLEAR CAUSE AT ANY RECENT MOMENT? DESCRIBE HOW YOU EXPERIENCED IT.

Yes, when I had the feeling that something had happened to my grandparents, I felt fear and sadness.

Fig. 3. Psychopathological Screening Module: Screening questionnaire for detection.

- The Psychopathological Screening Module comprises a series of open-ended questions designed to elicit spontaneous responses that reveal the student's emotional state. This form is accessible through AI-DASA and automatically adjusts to various screen sizes (see Figure 3).
- The Predictive Analysis Module utilizes the OpenAI API after converting students' responses into input for a Large Language Model (LLM) by employing prompt engineering techniques. It assesses three emotional dimensions: anxiety, depression, and stress. For each dimension, a binary classification is given, along with relevant keywords associated with the diagnosis (see Figure 5). The training process involves various techniques, including cycles and tokens, for refining the model's ability to interpret the data.
- Report Generation Module: The system processes the output from the semantic analysis and generates a PDF report. This report includes the detected emotional profile, a brief explanation of the results, identifying keywords, and self-care recommendations. The design of the report adheres to principles of clarity, neutrality, and an empathetic tone, which have been validated by mental health professionals (see Figure 4).
- Temporary Download/Notification Module: This module allows students to download their reports within a specified time frame or receive a download link via email. The information is not stored permanently on the server, in accordance with data privacy principles.

It is essential to note that AI-DASA was developed using the agile Scrum methodology, which facilitated iterative and incremental management throughout the design, development, and validation phases of the system. University students actively participated in this process by providing feedback on the clarity of the emotional assessment form and the usefulness of the reports generated. Additionally, mental health specialists played a crucial role in helping to define the emotional criteria used in the analysis.



HEALTH REPORT

September 29, 2024 – 13:18:48

Patient: JOSÉ SANTISTEBAN.

Diagnosis:
Possible Anxiety.

Justification of the Diagnosis:
The patient exhibits persistent nervousness, accompanied by physical symptoms such as tachycardia and a sense of fear, even in everyday situations without an apparent cause.

Recommendations:
Practice relaxation exercises, such as deep breathing techniques; consult with a therapist to address the underlying cause of anxiety.

Fig. 4. Report Generation Module: Report generated in PDF.

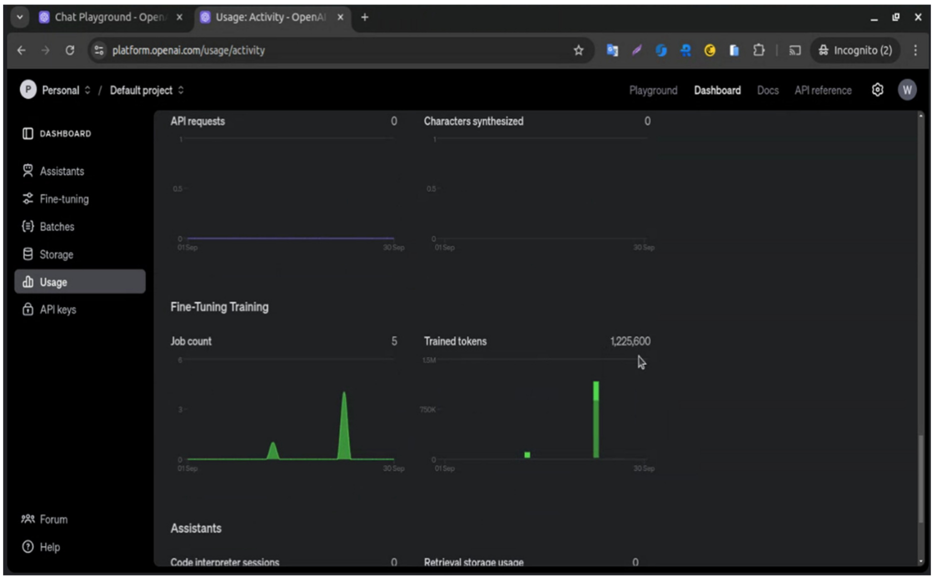


Fig. 5. AI-DASA Training: Training by cycles and tokens.

C. Validation

The AI-DASA system was validated in three distinct axes: efficiency, usability, and satisfaction. First, two psychologists specializing in mental health conducted an efficiency evaluation to compare AI-DASA's performance with the traditional assessment methods used by clinical psychologists. The mental health experts then completed a usability assessment using a questionnaire designed to measure the system's functionality, accessibility, and relevance. Finally, an overall satisfaction evaluation was conducted with 200 students from Engineering and Health Sciences. These students interacted with the AI-DASA system and provided feedback on their experiences and perceptions of the tool. This strategy enabled the assessment of AI-DAS's technical performance while also exploring its acceptance, practical usefulness, and institutional potential as a technological tool for emotional screening and support in university settings.

The two expert psychologists validated the system using a Likert-based survey instrument. The validation was exploratory. To ensure internal consistency, Cronbach's alpha was calculated at 0.88. A total of 200 anonymized responses were independently annotated according to the DSM-5 criteria. Inter-rater reliability was measured with Cohen's kappa (0.82). The dataset comprised 200 anonymized, open-ended texts collected from university students. Each entry was independently labeled by two licensed clinical psychologists, based on the criteria of DSM-5. In cases of disagreement (less than 6%), a third judgment was used to establish consensus, ensuring high inter-rater reliability (Cohen's kappa = 0.82).

1) Population

The system's efficiency and usability were evaluated by two experienced psychologists, each with 15 to 40 years of expertise in psychological diagnosis and the application of digital technologies in mental health. These experts assessed the system's effectiveness and accuracy, offering insights based on their extensive practical experience (see Table III).

TABLE III. DEMOGRAPHIC CHARACTERISTICS OF THE EXPERT JUDGMENT PARTICIPANTS

ID	Position	Academic background	Years of experience
E1	A clinical psychologist specialized in traditional psychological diagnosis	Bachelor's degree in clinical psychology, master's degree in psychodiagnostics	40
E2	A psychologist specialized in the validation of systems applied to psychological diagnosis	Bachelor's degree in psychology, master's degree in health psychology with a specialization in ICT	15

A total sample of 200 undergraduate students from the Universidad Peruana de Ciencias Aplicadas (UPC) in Lima, Peru, participated in the study. The participants were enrolled in Engineering and Health Sciences programs, ranged in age from 18 to 25 years, and 52% were women, ensuring a gender-balanced representation. Data collection was carried out using a digital form that included informed consent, which facilitated a structured and ethical data-gathering process (see Table IV).

TABLE IV. DEMOGRAPHIC CHARACTERISTICS OF THE PARTICIPANTS

Variable	Category	Frequency	Percentage (%)
Sex	Female	104	52.0
	Male	96	48.0
Age	18–20 years old	70	35.0
	21–23 years old	78	39.0
	24–25 years old	52	26.0
Major	Engineering	117	58.5
	Health Sciences	83	41.5
Academic level	5th–7th semester	94	47.0
	8th–10th semester	106	53.0

2) Instruments

To assess operational efficiency, a technical comparison was carried out between the AI-DASA system and the traditional evaluation process used by clinical psychologists. A technical-operational evaluation matrix was designed based on predefined criteria, which facilitated a structured comparison of both approaches (see Table V). This analysis examined several key variables, including the time required for implementation, the number of professionals involved, the necessity for external consultation, and the traceability of results. Additionally, the analysis was enhanced by reviewing historical records, gathering estimates from the professional team, and considering direct experiences with the implementation of the AI-DASA system.

TABLE V. TECHNICAL EVALUATION FOR EFFICIENCY ANALYSIS

Evaluation criterion	Description	Expected indicator	Evaluation source
Time per evaluation	Estimated duration of the manual clinical review process vs. AI-DASA	Reduction in analysis time	Clinical team estimates and system logs
Human resources involved	Number of people required to complete the manual process	Decrease in required personnel	Prior experience and AI-DASA pilot
External consultation required	Need for validation by additional experts or direct supervision	Reduction in frequency of additional consultations	Historical records and interviews
Organization and traceability	Level of systematization and record-keeping of the process	Improvement in documentation and access to auditable results	Direct observation and system output structure

The instrument was completed by the professionals in charge of the psychological support process at the university, allowing a direct and structured comparison of both methods. The results in Section IV indicate that the AI-DASA system significantly reduced the evaluation time from 48 hours to just 20 minutes, eliminated the need for multiple manual reviews, and facilitated an automated record of the entire process.

A survey was designed and distributed to experts to evaluate the usability of the AI-DASA system. The objective was to assess how easy it is to use and its practical effectiveness, drawing on insights from professionals with extensive experience in the field. This questionnaire consisted of 10 items specifically designed to evaluate the user experience with the tool (see Table VI). The questions were developed based on [25], which investigated usability and satisfaction testing in technological systems. The responses were collected using a 5-point Likert scale, where the participants indicated their level of agreement with the statements provided. The scale values were as follows: 1 for "Strongly disagree," 2 for "Disagree," 3 for "Neither agree nor disagree," 4 for "Agree," and 5 for "Strongly agree."

To enhance the interpretation of the results, the following score ranges were defined based on the average responses: an average score between 1.0 and 1.79 was considered very low; between 1.80 and 2.59 was regarded as low; between 2.60 and 3.39 was classified as moderate; between 3.40 and 4.19 was deemed high; and between 4.20 and 5.0 was interpreted as very high. These classifications provide a clear and detailed evaluation of the usability of the AI-DASA system.

The overall satisfaction assessment phase provided valuable insights into users' perceptions of the tool's usefulness, accessibility, and effectiveness in identifying emotional disorders. The questionnaire included a total of 20 questions, divided into four key dimensions (see Table VII). Each dimension was evaluated through five specific questions, allowing a comprehensive and detailed understanding of the user experience. This structure facilitated an in-depth assessment of overall perceptions regarding the usefulness, usability, and effectiveness of the AI-DASA system, offering a holistic perspective on its impact among students who used it. In the questionnaire given to the experts, a 5-point Likert scale was utilized, where 1 indicated "strongly disagree" and 5 denoted "strongly agree."

The instruments used in these three evaluations were designed to assess operational efficiency, usability, and user satisfaction. This comprehensive approach provides valuable insights into the functionality and acceptance of the AI-DASA system. By examining multiple dimensions, a solid foundation was established to understand the overall performance of the system and its potential for effective implementation in both educational and clinical settings. This creates a reference point for future enhancements and optimizations.

TABLE VI. EXPERT QUESTIONNAIRE FOR EVALUATING THE USE OF AI-DASA

Dimension	#	Question
Usability	Q01	Do you consider the AI-DASA system interface to be intuitive and easy to navigate for users?
	Q02	Do you believe that the wording and structure of the questions adequately allow for the identification of indicators of anxiety, depression, and stress?
	Q03	Do you think the system's interaction flow facilitates the psychological assessment process?
Functionality	Q04	Do you consider that the system's functionalities are aligned with the clinical objectives of early detection of mental disorders?
Clinical Utility	Q05	Do you think AI-DASA can be a useful tool to complement the work of mental health professionals?
Optimization	Q06	Do you agree that the automatic generation of reports helps optimize the time spent analyzing results?
Ethics and Confidentiality	Q07	Do you believe the system adequately respects ethical principles and confidentiality in psychological contexts?
Accessibility	Q08	Do you consider AI-DASA to be designed in a way that students can use it without confusion or misinterpretation?
Data visualization	Q09	Do you think the visualization of results is clear, understandable, and provides useful feedback for the user?
Overall recommendation	Q10	Would you recommend the use of AI-DASA as a support tool in educational settings for the early detection of mental disorders?

TABLE VII. QUESTIONNAIRE ADMINISTERED TO STUDENTS TO ASSESS SATISFACTION

Dimension	#	Question
Ease of Use	Q01	How easy was it for you to begin the emotional assessment process?
	Q02	How clear did you find the navigation within the platform?
	Q03	How understandable was the report generated by the system?
	Q04	Did the virtual assistant help you reflect on your emotional state?
	Q05	Did you find the overall interaction with the platform intuitive?
Content	Q06	Did the results accurately reflect your written responses?
	Q07	Was the feedback content relevant to your situation?
	Q08	Did the information provided help you understand your emotional state?
	Q09	Do you think the analysis was consistent with your symptoms or thoughts?
	Q10	Did the content encourage deeper reflection on your well-being?
Follow-up	Q11	Do you consider it useful to receive personalized recommendations?
	Q12	Do you think the system could provide follow-up for recurring cases?
	Q13	Would you like AI-DASA to notify or alert you about critical emotional states?
	Q14	Do you trust that AI-DASA can help ensure timely referral to a psychologist?
	Q15	Do you think the results can be stored for future review?
Satisfaction	Q16	Did you feel comfortable sharing your responses on the platform?
	Q17	Would you recommend AI-DASA to other students?
	Q18	Do you believe AI-DASA adds value to the student mental health and well-being services?
	Q19	Would you like your university to keep this tool available?
	Q20	How satisfied are you with your experience using AI-DASA?

3) *Experiment*

The experiment was carried out over three weeks in a controlled environment, following the university's safety and confidentiality protocols. The initial phase included training sessions for both experts and students. Experts participated in one-hour sessions, while students attended two-hour sessions. These training sessions aimed to ensure that all participants understood how to use the AI-DASA system effectively, as well as its purpose and functionality. In May 2025, an efficiency validation of the AI-DASA system was conducted with the participation of two expert psychologists via Zoom. They compared the effectiveness of the system with the traditional methods used for clinical assessments of anxiety, depression, and stress. Subsequently, a usability evaluation was conducted using a structured online questionnaire administered to the same university mental health experts. This questionnaire assessed key aspects such as ease of use, clarity of navigation, and overall functionality of the system.

The students accessed the AI-DASA web system from designated computers on campus, completed their registration by entering the required personal information, and began interacting with the platform. They explored the various modules of the system and received results generated by AI-DASA, which included the detection of anxiety, depression, and stress disorders. Finally, a 20-item questionnaire was administered to assess the level of satisfaction with the usability and effectiveness of the system. This phase provided valuable data on students' perceptions and experiences regarding the system. This series of activities allowed for the evaluation of the AI-DASA system's performance from various perspectives, ensuring its effective operation and a positive user experience.

III. RESULTS

A. *Efficiency Evaluation*

For the efficiency validation, a comparative analysis was performed between two assessment approaches: one based on a traditional manual detection process and the other utilizing the AI-DASA system. The goal was to identify improvements in key indicators, as presented in Table VIII.

TABLE VIII. PERFORMANCE COMPARISON BETWEEN TRADITIONAL EVALUATION AND THE AI-DASA SYSTEM

Efficiency indicator	Traditional process	AI-DASA system process	Improvement (%)	Observations
Total operating time	2880 minutes	20 minutes per form	99.3 %	Automated processing, significant reduction in time
Average human resources	2 psychologists per analysis	0 (automated model)	100 %	AI-DASA does not require human intervention in the initial assessment
Report review	Manual, with high variability	Automated and standardized	80 %	Homogeneous structure in all generated reports

The results show that AI-DASA facilitates agile, scalable processing with less reliance on qualified human resources, making it an effective option for early mental health screening in university environments. On average, the traditional process for evaluating and diagnosing disorders in students took approximately 48 hours per case. This time was distributed in interview sessions, individual analysis, and a thorough review of the data for each student. In AI-DASA, the evaluation time was significantly reduced to an average of just 20 minutes per case, encompassing both data entry and the automated execution of the detection process for anxiety, depression, and stress disorders, along with the generation of the corresponding report. This reduction in time represents a significant improvement in efficiency, leading to faster decision-making and timely management of mental health cases.

In the traditional approach to optimizing human resources, an average of two psychologists was required for each evaluation. They conduct interviews and perform customized clinical analyses for each student. In contrast, the AI-DASA system automates this entire process, eliminating the need for direct human involvement. This results in a 100% reduction in the human resources required during the diagnostic phase, thanks to the automated analysis, generation of results, and automatic issuance of reports in PDF format.

In addition to operational efficiency, the AI-DASA system was evaluated for its predictive performance. This assessment used a collection of free-form texts written by students, which were labeled by two clinical psychologists as a reference. The predictive model of AI-DASA accurately identified emotional indicators linked to disorders. Performance metrics were calculated using a binary classification approach for each emotional class (see Table IX).

TABLE IX. EVALUATION METRICS OF THE AI-DASA MODEL BY EMOTIONAL CLASS

Emotional class	Accuracy	Recall	Specificity	F1-score	AUC-ROC
Anxiety	0.94	0.89	0.91	0.90	0.93
Depression	0.93	0.85	0.78	0.84	0.89
Stress	0.94	0.84	0.87	0.83	0.90
Average	0.94	0.86	0.85	0.85	0.91

The results show that the model's accuracy for anxiety was 94%, with a sensitivity of 89% and an F1-score of 0.90, indicating a strong alignment with human evaluators. The model achieved an accuracy of 93% in identifying depression, although there was a slight decrease in specificity at 78%. This suggests a mild tendency to over-identify some ambiguous cases. For stress, the model obtained an accuracy of 94% with a sensitivity of 84%, demonstrating notable robustness in classifying moderate cases. The system achieved an average accuracy of 94% and an average F1-score of 0.85, demonstrating strong performance without the need for direct supervised training. Notably, AI-DASA excels at recognizing cases of anxiety and maintains strong performance in identifying depression and stress.

B. *Usability Evaluation by Experts*

Two psychologists evaluated the usability of the AI-DASA system from an expert perspective (Table V). After interacting with the AI-DASA system, the experts completed a questionnaire designed to assess various aspects of the platform's usability, including ease of use, clarity of navigation, content relevance, design appropriateness, and the potential impact on the early detection of psychological disorders (see Table X).

For each item, the mean of the scores assigned by the participants was calculated without excluding any responses. Subsequently, overall trends were determined based on the global average of the responses. To interpret the obtained values, a specific categorization scale was applied: 1.0 to 1.8 was considered very low, 1.8 to 2.6 low, 2.6 to 3.4 moderate, 3.4 to 4.2 high, and 4.2 to 5.0 very high.

TABLE X. USABILITY EVALUATION DIMENSION BY ITEM

Dimension	#	1	2	3	4	5	Average	Std. dev.
Usability	Q01	0	0	0	1	1	4.0	0.81
	Q02	0	0	0	2	0	4.5	0.58
	Q03	0	0	1	1	0	4.0	0.81
Functionality	Q04	0	0	0	2	0	4.5	0.58
Clinical usefulness	Q05	0	0	1	1	0	4.0	0.81
Operational efficiency	Q06	0	0	0	2	0	4.5	0.58
Ethics and confidentiality	Q07	0	0	0	2	0	4.5	0.58
Accessibility	Q08	0	0	1	1	0	4.0	0.81
Data visualization	Q09	0	0	0	2	0	4.5	0.58
General recommendation	Q10	0	0	1	1	0	4.0	0.81

The usability evaluation conducted by university mental health experts yielded very high scores across all dimensions assessed. The average scores remained above 4.0 on a scale of 1 to 5, with a particular emphasis on ease of use and system clarity. These findings reflect a high level of acceptance and a positive perception of the AI-DASA system from the experts' perspective.

C. *Student Satisfaction Evaluation*

This evaluation included 200 students who interacted with the system. To gain a comprehensive understanding of their experiences with the tool, a structured questionnaire containing 20 questions was distributed. These questions were organized into four key dimensions: ease of use, content, follow-up, and overall satisfaction. These dimensions were selected to assess both the students' direct interactions with the system and their overall perceptions of the tool's usefulness. The results in Table XI indicate a very high level of satisfaction across all evaluated dimensions. The students particularly appreciated the system's content, with an average score of 4.72, suggesting that they found the responses generated by AI-DASA to be relevant and helpful in understanding their emotional states. The follow-up dimension also received a strong rating, averaging 4.54. However, some students recommended improvements to the alert system and suggested the integration of more personalized follow-ups for recurring cases.

TABLE XI. AVERAGE SCORES BY DIMENSION AND ITEM IN THE SATISFACTION QUESTIONNAIRE

Dimension	Items	Average
Usability	Q01–Q05	4.58
Content	Q06–Q10	4.72
Follow-up	Q11–Q15	4.54
Satisfaction	Q16–Q20	4.73
Overall total	Q01–Q20	4.64

IV. DISCUSSION

A. *Efficiency Evaluation*

The results of the efficiency evaluation indicate that AI-DASA significantly improves upon the traditional assessment process carried out by clinical psychologists. With an impressive 99.3% reduction in operational time—from 2880 minutes down to just 20 minutes per evaluation—AI-DASA showcases exceptional automation capabilities. This not only improves operational efficiency but also enhances accessibility and scalability, enabling more students to be assessed in less time. Unlike traditional methods—such as using questionnaires like the PHQ-9 and GAD-7, which require direct professional involvement to interpret responses and generate results—AI-DASA offers a fully automated assessment process that significantly speeds up the procedure and boosts its efficiency [14]. AI-DASA eliminates the need for direct human intervention, reducing the involvement of human resources and the operational costs associated with diagnosis. Unlike traditional systems, which require time and specialized personnel, AI-DASA provides a more accessible and scalable alternative, particularly in countries like Peru, where access to mental health services is limited [9]. This automated approach addresses the limitations of conventional methods, positioning AI-DASA as an efficient and viable solution for low-resource educational settings.

B. Usability Evaluation by Mental Health Experts

The usability results from two expert psychologists indicate that AI-DASA excels in key areas such as ease of use, clarity of navigation, and clinical effectiveness. These scores were significantly higher for AI-DASA than for traditional systems, such as PHQ-9, which is often seen as rigid and impersonal due to its standardized format [26]. The main advantages were the ease of use and the straightforward navigation of the platform, enabling mental health professionals to adapt quickly without facing a steep learning curve. In contrast, other systems, such as MindLift, while effective, require more customization and adjustments from the user [27]. A key aspect of AI-DASA is its ability to maintain privacy and adhere to ethical standards when handling sensitive data. Other systems, such as MindLift, have faced criticism for integrating data from various sources without adequate regulation [12], but AI-DASA ensures that the collected information is managed ethically and transparently. This commitment helps foster greater acceptance among users and mental health professionals.

C. Evaluation of Students' Perceived Satisfaction

The satisfaction survey conducted with 200 students revealed that AI-DASA received an excellent rating from end users. The overall average score was 4.64 out of 5. The students particularly praised the clarity of the instructions and the system's ease of use. Compared to traditional assessment systems, such as PHQ-9 or GAD-7, which students often find impersonal and difficult to understand, AI-DASA is seen as a dynamic and user-friendly platform that promotes self-assessment and self-reflection, ultimately improving the overall user experience [28]. Students' willingness to recommend AI-DASA to others, with an average score of 4.5, highlights the platform's high value. This level of satisfaction is significantly higher than that reported for other automated systems, such as Woebot, which, despite its use in mental health care, has not achieved the same level of acceptance in terms of personalized interaction [18]. Feedback from students emphasizes that AI-DASA provides a more humanized and customized experience compared to other approaches, making the system not only useful but also enjoyable and accessible.

V. CONCLUSIONS

This study presents the design, implementation, and validation of the AI-DASA system, an advanced digital tool aimed at the early detection of emotional disorders such as anxiety, depression, and stress in university students. By employing NLP techniques—such as sentiment analysis, topic modeling, and semantic feature extraction—AI-DASA demonstrated its potential as a promising alternative to traditional assessment methods, offering significant improvements in terms of efficiency, accessibility, and accuracy. The results of the efficiency evaluation showed that AI-DASA significantly reduces the time required for the assessments, decreasing from 48 hours to only 20 minutes. Additionally, the system eliminates the need for direct human intervention, achieving a complete 100% reduction in the human resources required during the diagnostic phase. This optimization streamlines processes, enabling professionals to focus on tasks that deliver greater value.

University mental health experts showed high acceptance and positive evaluation of the AI-DASA system in terms of usability. The scores averaged more than 4.0 out of 5 in most areas evaluated, focusing on ease of use, clarity of navigation, and the system's value as a complementary tool for diagnosing emotional disorders. The experts emphasized the system's adherence to ethical and confidentiality principles, ensuring alignment with professional best practices in psychology. A satisfaction assessment conducted with 200 students yielded positive results. The students reported high levels of satisfaction, with an overall average score of 4.64 out of 5. They specifically highlighted the clarity of the instructions, the ease of use, and their willingness to recommend the system. This indicates that AI-DASA is considered a valuable and accessible tool that helps students explore their emotional health reflectively and efficiently.

This research contributes to the field of AI-based mental health screening by integrating zero-shot LLMs with structured prompt engineering for real-time emotional assessment. AI-DASA offers a scalable and accessible alternative to traditional psychological screening tools, demonstrating practical feasibility within low-resource academic environments. However, although AI-DASA ensures privacy-by-design and ethical data handling, the use of LLMs introduces inherent risks, such as biased predictions or emotional misclassification. These risks underscore the importance of maintaining human oversight in interpreting AI-generated outputs, particularly in sensitive domains such as student mental health.

AI-DASA is one of the first tools designed for Spanish-speaking university populations that uses generative AI to process open-ended responses and detect emotional symptoms. The use of lightweight technologies, such as Flask and SQLite, along with GPT-4 mini, makes it a novel and cost-effective solution for institutions lacking advanced technical infrastructure. AI-DASA offers an innovative approach to digital emotional assessment, with the potential to change how emotional disorders are addressed in educational settings. Its user-friendly design, efficient operation, and ethical framework make it a valuable tool to enhance the psychological well-being of university students, especially in situations where access to specialized mental health resources is limited.

Although this study yielded positive results, it also recognizes some limitations. The experiment lasted only three weeks, and being conducted at a single private university limits the ability to generalize the findings to other populations or educational settings. Although the system is intended to function as a guidance tool instead of a clinical diagnostic instrument, it is essential to convey this message in all user interactions. This clarity will help prevent any misunderstandings about the nature of the diagnoses the system provides.

Future studies may expand the sample size and deploy AI-DASA across multiple institutions in diverse regions. Comparative evaluations between GPT-4 mini and newer models could refine performance. In addition, integrating human-in-the-loop feedback mechanisms can enhance interpretability and reduce the risk of misclassification in critical mental health scenarios. Furthermore, exploring the integration of AI-DASA with real-time psychological counseling services could provide closer follow-up and support for students. In general, AI-DASA represents a foundational step toward the integration of ethical and context-aware AI systems in university wellness programs. Its long-term potential lies in enabling scalable and proactive mental health monitoring strategies that complement institutional support systems and contribute to student well-being.

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REPRODUCIBILITY

Although the source code is not publicly available due to the University's data protection policy, the authors can provide pseudocode, API request structure, and prompt templates upon request.

DATA AVAILABILITY

The datasets generated and analyzed during this study are internal and contain sensitive mental health data from university students. According to ethical guidelines and institutional policy, these data are confidential and not publicly available. Access to the data is restricted and may be granted only upon reasonable request and with appropriate ethical approvals.

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