

DIAGNOSTIC ACCURACY AND RELIABILITY OF GEMINI AI FOR MENTAL HEALTH SCREENING

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Abstract

Mental health problems among university students are increasing, while stigma and limited access to professional services often delay help-seeking. Artificial intelligence (AI)-based screening tools may provide an accessible approach for early mental health detection. This study aimed to evaluate the diagnostic accuracy and reliability of Gemini AI for mental health screening within Indonesia's SATU SEHAT framework. A pilot cross-sectional diagnostic accuracy study was conducted among 63 undergraduate students. Participants completed mental health screening using both Gemini AI and the SATU SEHAT platform. Diagnostic performance was assessed using receiver operating characteristic (ROC) analysis, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), overall accuracy, and Cohen's Kappa coefficient. Gemini AI demonstrated excellent discriminative ability with an area under the curve (AUC) of 0.957 (95% CI: 0.89–1.00). Sensitivity was 86.36%, specificity 97.56%, PPV 95.00%, NPV 93.02%, and overall accuracy 93.65%. Agreement with the SATU SEHAT reference standard was almost perfect (Cohen's Kappa = 0.857, $p < 0.001$). Gemini AI showed high diagnostic accuracy and reliability for early mental health screening. These findings suggest that AI-assisted screening may complement existing digital mental health services by supporting early identification of individuals at risk and providing a foundation for larger validation studies.

Keywords: Artificial Intelligence, Health, Mental



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INTRODUCTION

Mental health and psychological well being are closely related concepts and are frequently used interchangeably, although the term mental health is more widely adopted in international literature (Kementerian Kesehatan, 2024). According to the World Health Organization, defines mental health as a condition of well being in which individuals realize their abilities, effectively manage everyday stress, engage in productive work, and actively contribute to (Presiden RI, 2023).

This perspective highlights that mental health extends beyond the mere absence of mental illness, encompassing overall psychological resilience and healthy social functioning. At the national level, Indonesia's Law number 17 of 2023 on Health defines mental health as a state in which individuals can

grow and function physically, mentally, spiritually, and socially, allowing them to recognize their capacities, cope with stress, work productively, and engage actively in society. This framework places mental health on an equal footing with physical health as a fundamental component of overall well-being. Mental health problems are commonly marked by prolonged mood disturbances, diminished interest or pleasure in usual activities, heightened anxiety, and reduced ability to function in daily life. Such conditions can interfere with academic performance, occupational productivity, and social interactions. In more serious situations, mental health disorders may elevate the risk of self-harm and suicidal behavior (Kementerian Kesehatan, 2024). These findings are consistent with international evidence showing that depression, anxiety, and psychological distress are associated with reduced academic achievement, impaired social functioning, and lower quality of life among university students (Richardson, Elliott, & Roberts, 2017; Bruffaerts et al., 2018).

Several studies have indicated that unmanaged stress may develop into mental health disorders such as anxiety and depression, which can subsequently lead to decreased academic performance among university students (Rivaldi Al, 2024) (Pascoe, Hetrick, & Parker, 2020). Common symptoms include persistent negative mood, loss of interest, excessive guilt, fatigue, impaired concentration, appetite disturbances, and suicidal ideation. In addition to psychological symptoms, individuals may also experience somatic complaints such as gastrointestinal discomfort, headaches, respiratory symptoms, or unexplained pain without clear organic causes. This condition is often referred to as masked depression, in which somatic manifestations are more prominent than emotional complaints (Kementerian Kesehatan, 2024). Similar findings have been reported in recent studies showing that depressive disorders frequently present with somatic symptoms, including fatigue, pain, gastrointestinal complaints, and other physical manifestations, which may contribute to delayed recognition and treatment of mental health conditions, particularly among young adults and student populations (Leathers et al., 2021; Guo et al., 2022).

In 2023 Indonesia Health Survey, the national prevalence of depression among individuals aged 15-24 years was reported at 1.4%. The prevalence was higher among females (2.8%) compared to males (1.1%), and this age group predominantly corresponds to the university student population (Anggita, 2024). University students experiencing mental health disorders require a comprehensive support system, including social, family, community, and peer support. Such support plays a crucial role in encouraging students with mental health problems to remain motivated in seeking professional care, adhering to prescribed treatments, and recognizing early signs of recurrence. Sustained support from multiple stakeholders is essential in promoting recovery and preventing relapse.

Previous studies have demonstrated that social support is associated with improved psychological well-being, greater engagement with mental health services, and reduced psychological distress among university students experiencing mental health difficulties. In addition, peer-support initiatives and supportive campus environments have been recognized as important strategies for facilitating help-seeking behaviors and enhancing recovery outcomes among students with mental health concerns (Pointon-Haas et al., 2023; Vicary et al., 2025).

Addressing mental health issues among students should not only involve curative and rehabilitative interventions but also incorporate promotive and preventive strategies to enhance resilience and well-being. Recent evidence indicates that strong social support and connectedness are associated with better psychological outcomes, reduced distress, and increased help-seeking behaviors among university students (Alsubaie, Stain, Webster, & Wadman, 2019). Without appropriate support and interventions, mental health disorders can lead to a decline in productivity, including reduced academic performance, may increase the risk of suicidal ideation and behavior among affected students (Mortier et al., 2018; Anggita, 2024).

Despite the growing recognition of mental health problems among young people, help-seeking behavior remains substantially delayed. Treatment coverage in such cases remains critically low, reaching only 12.7%. Only one of the primary contributing factors is the persistent stigma and negative labeling associated with mental health conditions. Stigma may originate both internally (self-stigma) and externally, including from communities, society, institutions, the surrounding environment, and even health professionals. This situation underscores the urgent need to strengthen mental health literacy, expand community education, and implement broader societal interventions, particularly within higher education settings. Recent evidence indicates that stigma, poor mental health literacy, and limited awareness of available services remain among the most significant barriers preventing young people and university students from seeking professional psychological support, while improved mental health

literacy is associated with greater willingness to seek help and earlier intervention (Huff et al., 2024; Koutra, Pantelaiou, & Mavroeides, 2024; Libano et al., 2024; Lui, Sagar-Ouriaghli, & Brown, 2024).

Universities play a strategic role in fostering supportive environments for students experiencing psychological distress. In this context, the role of a first aider in mental health should not be limited to lecturers or student affairs officers, but should extend to the entire academic community. When members of the university community possess adequate mental health literacy, early detection and timely referral become more feasible. However, students' mental health literacy levels remain suboptimal and require further improvement. Higher education institutions therefore represent a critical setting for promoting mental well being and developing effective stress management strategies among students (Nazira et al., 2022; Kementerian Kesehatan, 2024). Recent studies have emphasized that improving mental health literacy within university communities can reduce stigma, strengthen help-seeking intentions, facilitate early recognition of psychological problems, and enhance access to appropriate support services for students (Gao et al., 2024; McCabe et al., 2024).

Institutional efforts including the provision of social skills development programs, enhancement of peer and community support networks, and the promotion of constructive social interactions, especially among first year students have been recognized as key preventive approaches to reduce psychological distress (Prasetio & Rahman, 2019). These findings are consistent with international evidence indicating that mental health stigma, low mental health literacy, and limited help-seeking behaviors remain significant barriers to accessing mental health services among university students, highlighting the importance of campus-wide mental health promotion initiatives (Kutcher, Wei, & Coniglio, 2016; Gorczynski et al., 2017; Ebert et al., 2019). These findings are supported by recent evidence showing that poor mental health literacy, self-stigma, and negative attitudes toward psychological treatment remain major barriers to help-seeking among university students, while improved mental health literacy is associated with greater willingness to seek professional support and earlier intervention. Universities are therefore important settings for implementing mental health promotion programs aimed at reducing stigma and strengthening help-seeking behaviors among students (Ma, Burn, & Anderson, 2023; Koutra et al., 2024; Yang et al., 2024).

Early identification of mental health problems involves assessing behavioral patterns, noticeable changes, symptom duration, proportionality of emotional responses, functional impairment, environmental influences, and clinical manifestations of psychological disorders. However, access to early screening tools remains limited and not all individuals are aware of how to obtain or utilize such tools effectively. In many cases, mental health continues to receive less attention compared to physical health, leading to delayed identification and intervention. In response to these challenges, researchers have explored the development of Artificial Intelligence based early detection tools that can be accessed through personal digital devices. AI driven platform offer mental health privately without fear or negative labeling. The incorporation of AI into mental health care has been reported to enhance service accessibility, minimize stigma related barriers, and deliver timely psychological assistance (Khairan & Habib, 2025). Emerging evidence suggests that AI assisted mental health interventions can contribute to reductions in depressive symptoms, with users reporting high levels of satisfaction when engaging with digital tools (Reyes-Portillo et al., 2025). Furthermore, recent studies have highlighted that AI-based screening and digital mental health technologies can support early risk identification, improve access to mental health services, and facilitate scalable interventions for populations with limited access to conventional care (Fiske, Henningsen, & Buyx, 2019; Halbreich, 2023). The recent studies suggest that digital mental health technologies and AI-enabled systems may facilitate early risk identification, improve access to psychological support, and provide scalable interventions for populations facing barriers to conventional mental health service (Lattie, Stiles-Shields, & Graham, 2022; Philippe et al., 2022).

Nevertheless while AI demonstrates promising potential in mental health screening and early detection, it is intended to serve as a supportive adjunct to professional services not as a substitute for clinical care. Ethical aspect such as professional accountability, data protection, methodological consistency, and concerns related to privacy and algorithmic bias must be carefully addressed to enhance the credibility and practical value of AI based mental health interventions (Humayun et al., 2025; Maryani et al., 2026).

Although previous studies have demonstrated the potential of artificial intelligence (AI) and digital mental health tools in improving access to psychological screening and support, evidence regarding the diagnostic accuracy and reliability of generative AI systems such as Gemini remains limited, particularly when compared with established digital health screening platforms. Furthermore,

most existing studies have focused on machine learning models, chatbots, or multimodal AI approaches, while the performance of large language model-based systems for mental health screening has not been adequately validated in real-world settings. Given the increasing prevalence of mental health problems among university students and the growing adoption of AI technologies in healthcare, evaluating the accuracy and reliability of Gemini is essential before its broader implementation as an early screening tool. Therefore, this study aimed to evaluate the diagnostic accuracy, discriminative ability, and agreement of Gemini AI for mental health screening using Indonesia's *SATU SEHAT* platform as the reference standard.

RESEARCH METHOD

This study employed a pilot cross-sectional diagnostic accuracy design to evaluate the performance of a Gemini-based Artificial Intelligence (AI) mental health screening system using Indonesia's *SATU SEHAT* platform as the reference standard. The study assessed the diagnostic accuracy and agreement between both screening methods through statistical measures including receiver operating characteristic (ROC) analysis and Cohen's Kappa coefficient. The target population comprised all first-year university students enrolled at Akademi Refraksi Optisi dan Optometri GAPOPIN during the study period. Participants were recruited using a consecutive sampling technique, in which all eligible students who met the inclusion criteria were invited to participate until the required sample size was achieved. The inclusion criteria were, registered first-year university students; completed the Gemini AI mental health screening; completed the *SATU SEHAT* mental health assessment; provided written informed consent. The exclusion criteria were: incomplete assessment data; missing *SATU SEHAT* reference classification; withdrawal of consent during the study. A total of 63 students met the eligibility criteria and were included in the final analysis.

The study was conducted through the following procedures: Eligible participants received an explanation regarding the study objectives and procedures and signed written informed consent; Participants completed the Gemini AI-based mental health screening using standardized instructions; The Gemini system automatically processed questionnaire responses and generated a continuous mental health risk score for each participant; Participants subsequently completed the mental health assessment available in Indonesia's *SATU SEHAT* application; *SATU SEHAT* classifications were retrieved independently and used as the reference standard without knowledge of the AI screening results; Gemini continuous scores were analyzed using ROC curve analysis to determine the optimal cut-off value based on Youden's Index before being classified into positive and negative screening results; All participant data were anonymized prior to statistical analysis.

Two digital assessment tools were employed in this study. The index test was a Gemini-based Artificial Intelligence screening system that analyzed participants' responses to a structured mental health questionnaire and generated a continuous mental health risk score. The optimal cut-off value was determined using ROC analysis with Youden's Index to classify participants into positive or negative screening categories. The reference standard was the mental health screening classification recorded within Indonesia's *SATU SEHAT* platform developed by the Ministry of Health of the Republic of Indonesia. Data collection was performed sequentially. Participants first completed the Gemini AI screening followed by the *SATU SEHAT* assessment. All screening results were coded and anonymized before statistical analysis to ensure participant confidentiality. Table 1 presents the data collection instruments and variables used in this study, including the corresponding indicators, measurement scales, and expected outputs for each variable.

Table 1. Data Collection Instrument Grid

Variable	Instrument	Indicator	Scale	Output
Mental health risk score	Gemini AI Screening System	AI-generated screening score	Continuous	Numerical score
Mental health classification	Gemini AI Screening System	Positive/Negative classification	Nominal	Category
Mental health status	SATU SEHAT Platform	Mental health screening result	Nominal	Positive/Negative
Age	Demographic Form	Participant age	Ratio	Years
Gender	Demographic Form	Sex	Nominal	Male/Female

Statistical analyses were performed using IBM SPSS Statistics version 20. Descriptive statistics were used to summarize participant characteristics. The diagnostic accuracy of the Gemini AI system was evaluated using receiver operating characteristic (ROC) curve analysis, and the area under the curve (AUC) with its 95% confidence interval (CI) was calculated to assess discriminative ability. The optimal cut-off score was determined using Youden's Index (Sensitivity + Specificity - 1). Based on this threshold, continuous AI scores were converted into binary classifications (positive or negative). Diagnostic performance was assessed by calculating sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and overall accuracy using *SATU SEHAT* classifications as the reference standard. Agreement between Gemini AI and *SATU SEHAT* classifications was evaluated using Cohen's Kappa coefficient. Kappa values were interpreted according to the Landis and Koch classification, where values of 0.81–1.00 indicate almost perfect agreement, 0.61–0.80 substantial agreement, 0.41–0.60 moderate agreement, 0.21–0.40 fair agreement, and values below 0.20 slight or poor agreement. Statistical significance was established at $p < 0.05$.

RESULTS AND DISCUSSION

To evaluate the diagnostic performance of Gemini AI for mental health screening, receiver operating characteristic (ROC) analysis and diagnostic accuracy measures were calculated using *SATU SEHAT* classifications as the reference standard. The results are presented in Table 2.

Table 2. Diagnostic Accuracy Measures

Measures	Value (%)	CI 95%
AUC	0.957	0.89-1.00
Sensitivity	86.36	65.1-95.6
Specificity	97.56	87.4-99.9
Positive Predictive Value (PPV)	95.00	75.1-99.9
Negative Predictive Value (NPV)	93.02	80.9-97.8
Accuracy	93.65	84.5-97.5
Youden's Index	0.84	-
Cohen's Kappa	0.857	$P < 0.0001$

As shown in Table 2, the Gemini AI system demonstrated excellent discriminative ability, with an AUC of 0.957 (95% CI: 0.89–1.00). This finding indicates a strong capacity to distinguish between students classified as at risk and not at risk of mental health problems according to the *SATU SEHAT* reference standard. The model achieved a sensitivity of 86.36% and specificity of 97.56%, suggesting strong performance in correctly identifying both positive and negative cases. The high specificity indicates a very low false-positive rate, which is particularly important in mental health screening contexts. The positive predictive value (PPV) was 95.00%, while the negative predictive value (NPV) reached 93.02%. Overall diagnostic accuracy was 93.65%, indicating that the majority of classifications generated by Gemini AI were consistent with the reference standard. Agreement analysis further demonstrated almost perfect agreement between Gemini AI and *SATU SEHAT* classifications (Cohen's $\kappa = 0.857$, $p < 0.001$).

To further illustrate the discriminative performance of the Gemini AI model, the ROC curve is presented in Figure 1.

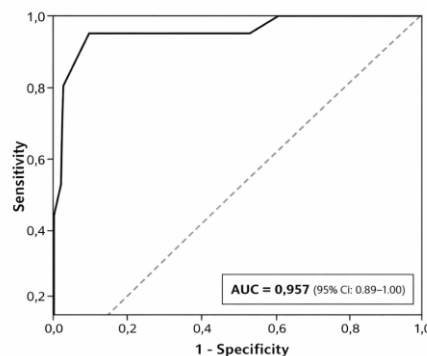


Figure 1. Receiver Operating Characteristic (ROC) curve of the AI based mental health risk detection model.

As presented in Figure 1, the ROC curve demonstrates excellent diagnostic performance of the Gemini AI screening model. The area under the curve (AUC) was 0.957 (95% CI: 0.89–1.00), indicating excellent discriminative ability. An AUC value above 0.90 is generally considered outstanding, suggesting that the model was highly effective in distinguishing participants classified as positive and negative according to the *SATU SEHAT* screening framework.

The findings of this study indicate that Gemini AI has substantial potential as an early mental health screening tool. The combination of high diagnostic accuracy, excellent discriminative ability, and almost perfect agreement with the *SATU SEHAT* framework suggests that AI-assisted screening may support rapid identification of individuals at risk of mental health problems. These findings are particularly relevant in university settings, where limited mental health resources and stigma often hinder timely access to professional support (Feng et al., 2025; Umam, Suranata, & Lestari, 2025).

Our pilot study demonstrated that the Gemini base AI system achieved strong classification performance for mental health risk screening (AUC = 0.957, sensitivity = 86,4%, specificity = 97,6%), with almost perfect agreement with the reference framework (Cohen's K = 0,857). These results indicate that the model can distinguish between students at risk of stress and those not at risk with high accuracy, underscoring its potential as a screening tool in digital health contexts. The high AUC value is consistent with recent evidence showing that AI models can achieve excellent discriminative ability when multi-modal data or advanced algorithms are leveraged for mental health screening tasks. For example, a systematic meta-analysis of AI-assisted methods reported pooled AUCs as high as 0.95 for depression screening across multiple modalities (EEG, behavioral signals, speech) in recent AI research, highlighting the feasibility of AI-driven classification in affective disorders (Shatte, Hutchinson, & Teague, 2019; Pires, Mourão, & Santos, 2024; Wang et al., 2025a).

Furthermore, recent reviews of large language models (LLMs) in mental health have highlighted their potential role in early screening, digital mental health support, and risk identification. Although concerns regarding transparency, bias, and clinical validation remain, current evidence suggests that generative AI systems may serve as valuable complementary tools within digital mental health ecosystems when used alongside established screening frameworks and professional oversight (Guo et al., 2024; Bucher et al., 2025; Jin et al., 2025). Emerging evidence also indicates that generative AI may improve access to mental health services by enhancing scalability, personalization, and early risk detection. Nevertheless, researchers continue to emphasize the importance of ethical governance, safety monitoring, explainability, and human oversight to ensure responsible implementation in clinical and public health settings (Obradovich et al., 2024; Wang, Zhou, & Zhou, 2025).

Our findings align with emerging evidence in the literature that AI-based models show strong performance in mental health detection. A recent meta-analysis of deep learning models for depression detection using speech features reported pooled AUC values up to 0.91, with sensitivities and specificities in good ranges similar to those observed in our study (Liu et al., 2024). Another systematic review on AI models for wearable depression prediction found pooled sensitivity and specificity for depression screening between 61%-87% and 73%-93%, respectively, illustrating that high performance is achievable but variable across contexts (Abd-Alrazaq et al., 2023). Broad reviews of AI in mental health also highlight the increasing accuracy of AI models in detecting and classifying mental health conditions across diverse datasets, suggesting that our results fit within the broader trend of effective AI screening performance (Cruz-Gonzalez et al., 2025). Furthermore, machine learning models applied to university student populations have demonstrated promising performance in detecting depression, anxiety, and stress, highlighting the potential value of AI-assisted approaches for early mental health assessment in academic settings (Lawrence et al., 2024; Wang et al., 2025b).

In contrast to some earlier voice-biomarker studies that reported moderate classification accuracy for depression and stress detection, more recent research emphasizes the importance of multimodal data integration and explainable machine learning approaches to improve both predictive performance and interpretability in mental health applications. Recent systematic reviews have highlighted that combining facial expressions, speech characteristics, behavioral signals, and physiological indicators generally results in higher diagnostic accuracy compared with single-modality approaches (Nguyen et al., 2023; Esteban-Burgos et al., 2024).

Furthermore, explainable artificial intelligence (XAI) has emerged as an important strategy for improving transparency, interpretability, and clinical trust in AI-assisted mental health applications (Jin et al., 2023; Kerz et al., 2023; Mienye et al., 2024). For example, reviews of AI-based recognition of facial and micro-expressions in mental and neurological conditions reported that many models achieved

AUC values above 0.90, suggesting robust discriminative power when combining multiple data features (Ghafari, 2025). Overall, while methodological heterogeneity and dataset variability remain common challenges in AI applications for mental health screening, the emerging trend from recent empirical and review studies supports the feasibility of AI systems, like the one evaluated in this research, to achieve excellent classification performance comparable to other machine learning applications in digital health.

The findings of this study have practical implications for the development of digital mental health services. Given its high diagnostic performance, Gemini AI may serve as a complementary screening tool to support early identification of students at risk of mental health problems. Integration of AI-assisted screening into existing digital health ecosystems, including the *SATU SEHAT* platform, may enhance accessibility, reduce screening burden, and facilitate timely referral for professional assessment. However, AI-based screening should be considered a supportive tool rather than a replacement for clinical evaluation.

This study has several limitations. First, the sample size was relatively small and limited to undergraduate students, which may restrict the generalizability of the findings. Second, the study was conducted within a single institutional setting and therefore may not represent broader populations. Third, the evaluation focused on screening performance and did not assess long-term clinical outcomes. Future studies should include larger and more diverse samples, involve multiple institutions, and evaluate the effectiveness of Gemini AI across different demographic and clinical contexts.

CONCLUSION

This study evaluated the diagnostic accuracy and reliability of a Gemini-based artificial intelligence system for mental health risk screening within Indonesia's *SATU SEHAT* digital health framework. The findings demonstrated excellent discriminative performance ($AUC = 0.957$), high sensitivity and specificity, and almost perfect agreement with the reference standard (Cohen's $\kappa = 0.857$). These results indicate that Gemini AI can accurately identify individuals at risk of mental health problems and may serve as a reliable tool for early mental health screening. Beyond its diagnostic performance, this study provides preliminary evidence supporting the integration of generative AI into digital mental health ecosystems. The findings suggest that AI-assisted mental health screening can function as a complementary approach to existing digital health services, facilitating scalable, accessible, and timely identification of individuals at risk. This study contributes to the emerging concept of AI-assisted screening within national digital health infrastructures and highlights its potential to support preventive mental health strategies and future digital health innovation.

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AUTHOR CONTRIBUTIONS

Author FM and MWB developed the research concept and methodology and also conducted the quantitative data analysis using SPSS and interpreted the findings. Author MS translator, Author OC and BR assisted in data collection and validation. Author NZ and PG contributed to literature review, manuscript drafting, and critical revisions. All authors reviewed, edited, and approved the final manuscript. FM = Febri Maryani; MWB= M. Wahyu Budiana; MS= Murni Marlina Simarmata; NZ= Nisa Zakiati Umami; PG= Putri Ghanim Septia Habiba; BR= Bunyamin Rizki Abdillah; OC= Opep Cahya Nugraha.

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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