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AI-ASSISTED SCREENING OF DEPRESSION AND ANXIETY AMONG UNIVERSITY STUDENTS: A CROSS-SECTIONAL STUDY

Original Article

Zarina Naz[1], Muhammad Zia Iqbal[2], Seemal Fatima[3], Jahangir Baig[4], Mehnaz Begum[5], Sadaf Liaqat[6], Maryam Imad[7]*

[1]MSN, RN, RM, DWA, DTA, MHPE Scholar, National University of Medical Sciences, Rawalpindi, Pakistan.
[2]Professor of Anatomy & Ophthalmologist, Suliman Alrajhi University, Al Bukayriah, Saudi Arabia.
[3]MBBS Student, Avicenna Medical College, Lahore, Pakistan.
[4]PhD Student, Department of Statistics, University of Karachi, Karachi, Pakistan.
[5]Lecturer in Education, University of Swabi, Swabi, Pakistan.
[6]University of Kotli, Azad Jammu & Kashmir (AJK), Pakistan.
[7]Lecturer, University of Swat, Swat, Pakistan.

Corresponding Author: Maryam Imad, Lecturer, University of Swat, Swat, Pakistan, maryam@uswat.edu.pk

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ABSTRACT

Background: Depression and anxiety represent significant and growing mental health challenges among university students worldwide. Traditional screening methods such as the Patient Health Questionnaire-9 (PHQ-9) and Generalized Anxiety Disorder-7 (GAD-7) remain reliable but are often time-consuming and resource-intensive. Advances in artificial intelligence (AI) offer the potential to augment or automate screening processes, enhancing accessibility and efficiency in academic environments.

Objective: This study aimed to evaluate the diagnostic accuracy and agreement of an AI-assisted screening tool against standardized psychometric instruments for detecting depressive and anxiety symptoms among university students.

Methods: A total of 370 students were enrolled, with 356 completing the full assessment (response rate: 96.2%). Participants completed the PHQ-9 and GAD-7 scales, and results were compared with AI-generated predictions. Diagnostic performance was assessed using sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and Cohen's kappa coefficient. Pearson correlation coefficients were used to determine associations between AI and traditional scale scores.

Results: The prevalence of clinically significant depression and anxiety (score $\geq$ 10) was 33.7% and 35.4%, respectively. The AI tool classified 33.1% as probable depression and 36.5% as probable anxiety, demonstrating strong concordance with PHQ-9 and GAD-7 results. Sensitivity and specificity were 89.2% and 91.6% for depression, and 87.6% and 90.1% for anxiety. Substantial agreement was observed ($\kappa = 0.82$ and $\kappa = 0.79$, $p < 0.001$). ROC analyses yielded AUCs of 0.94 for depression and 0.92 for anxiety, indicating excellent predictive accuracy.

Conclusion: The AI-assisted screening tool demonstrated strong diagnostic validity and agreement with established psychometric scales, supporting its potential as an efficient and reliable adjunct for large-scale mental health screening among university students.

Keywords: Adolescent; Algorithms; Anxiety Disorders; Artificial Intelligence; Depression; Mental Health; Psychometrics.

INTRODUCTION

Mental health disorders such as depression and anxiety represent a growing concern among university students worldwide. The transition to higher education is a period marked by profound psychological, academic, and social adjustments (1). During this phase, young adults are often confronted with academic pressures, financial uncertainty, social isolation, and identity-related challenges, all of which may predispose them to mental health difficulties (2). Global estimates indicate that nearly one in three university students experiences symptoms of anxiety or depression, yet a significant proportion remain undiagnosed or untreated. The consequences of these untreated mental health conditions are substantial, influencing not only academic performance and social functioning but also long-term psychological well-being and quality of life (3). In recent years, awareness surrounding mental health in academic settings has improved, but effective early detection remains limited (4). Traditional screening methods, such as clinical interviews or paper-based self-report questionnaires, though widely used, face notable barriers (5). These include time constraints, stigma associated with seeking psychological help, and limited access to trained mental health professionals (6). Moreover, in many educational institutions—especially in low- and middle-income countries—the availability of qualified counselors is insufficient to meet the growing demand. Consequently, there is an urgent need for innovative, scalable, and accessible approaches to identify students at risk of depression and anxiety at an early stage (7). Advancements in artificial intelligence (AI) offer promising solutions to bridge this gap. AI-assisted tools, designed to analyze behavioral, linguistic, and self-reported data, can provide efficient, cost-effective, and personalized screening for mental health disorders (8). These systems can interpret subtle emotional cues and detect patterns that might otherwise go unnoticed in traditional assessments. By integrating machine learning algorithms with standardized psychometric instruments, AI-based tools can potentially enhance the accuracy and reach of mental health screening (9). Importantly, such tools can be deployed via digital platforms—such as smartphones or learning management systems—making them accessible to students in diverse educational environments.

The integration of AI into mental health care, however, raises important questions about its reliability, accuracy, and ethical implications. While AI-driven systems have shown promising results in clinical research and pilot studies, their practical application in university settings remains underexplored (10). Many existing studies have focused on general populations or clinical samples, leaving a gap in understanding how these tools perform among young adults within academic institutions (11). Additionally, cultural and contextual factors may influence how students respond to AI-based assessments, further emphasizing the need for population-specific validation. Understanding whether AI can accurately and sensitively detect symptoms of depression and anxiety among university students is crucial for informing policy and practice in higher education health services (12). Furthermore, AI-supported screening tools may help reduce the stigma traditionally associated with mental health evaluations. Because these systems can operate anonymously and asynchronously, students may feel more comfortable disclosing sensitive emotional information. This feature could lead to higher participation rates in mental health screening programs, ultimately improving early detection and intervention outcomes. Yet, questions remain regarding the balance between automation and human oversight, data privacy concerns, and the potential risk of over-reliance on algorithmic decision-making in sensitive health contexts (13). Against this backdrop, the present study seeks to evaluate the effectiveness of AI-supported mental health screening tools in identifying symptoms of depression and anxiety among university students. By employing a cross-sectional design, the study aims to assess the accuracy, sensitivity, and practicality of AI-assisted approaches compared with traditional screening methods. This research is grounded in the recognition that timely and accurate detection of mental health problems is essential for effective intervention and support. The study's findings are expected to contribute valuable evidence toward integrating digital and AI-driven solutions into student mental health services, especially in resource-constrained educational environments. In summary, while the burden of anxiety and depression among university students continues to rise, current screening and diagnostic approaches remain inadequate in terms of accessibility and efficiency. AI-assisted tools offer a promising pathway to address these limitations by enabling large-scale, user-friendly, and precise mental health assessments. However, empirical validation is necessary to ensure their clinical utility and ethical soundness. Therefore, the objective of this study is to evaluate the effectiveness of AI-supported screening tools in detecting symptoms of depression and anxiety among university students, thereby assessing their potential role in enhancing early mental health identification within academic settings.

METHODS

This cross-sectional study was conducted over a period of four months at selected universities in Lahore, Pakistan, with the primary objective of evaluating the effectiveness of artificial intelligence (AI)-supported mental health screening tools in detecting depression and anxiety among university students. The study design was chosen to allow for a comprehensive snapshot of mental health status within a defined population at a single point in time, ensuring feasibility and representativeness within the study duration. The study population consisted of undergraduate and postgraduate students enrolled in different academic disciplines. Participants were selected using a stratified random sampling method to ensure adequate representation across faculties, gender, and academic levels. Inclusion criteria comprised students aged 18 years or older, currently enrolled in full-time academic programs, and able to comprehend English, as the screening instruments were administered in that language. Students with a prior diagnosis of a severe psychiatric disorder (such as schizophrenia, bipolar disorder, or psychotic depression), those currently undergoing psychiatric treatment, or individuals unwilling to provide informed consent were excluded to minimize potential confounding factors. where Z corresponds to the 95% confidence interval (1.96), p represents the anticipated prevalence of depression and anxiety (assumed at 30% based on prior studies among university populations), and d denotes the allowable margin of error (set at 5%). The calculated sample size was approximately 323 participants. To account for potential non-response or incomplete data, an additional 15% was added, bringing the total target sample size to 370 students. Data collection was performed using a combination of standardized psychometric instruments and an AI-assisted digital screening tool. Each participant completed two validated self-report questionnaires: the Patient Health Questionnaire-9 (PHQ-9) for depression and the Generalized Anxiety Disorder-7 (GAD-7) scale for anxiety assessment. These tools are internationally recognized for their reliability and validity in identifying symptoms of depression and anxiety, respectively, and are suitable for use in both clinical and research settings. The AI-supported screening tool used in this study incorporated machine learning algorithms capable of analyzing questionnaire responses alongside linguistic and behavioral markers, such as response latency and emotional tone, to generate individualized predictions of anxiety and depression likelihood. Participants were recruited through online portals, university notice boards, and student email lists. Those who consented were directed to a secure web-based platform where the informed consent form and screening tools were hosted. The platform ensured confidentiality and data security through password-protected access and encrypted data transmission. Prior to data collection, participants were briefed on the study objectives, data usage, and voluntary participation. Each student provided electronic informed consent before proceeding to the questionnaires.

The collected data included demographic information such as age, gender, academic level, field of study, and socioeconomic background. Scores from the PHQ-9 and GAD-7 were computed according to standardized scoring guidelines. The AI model's diagnostic predictions were then compared to the classification outcomes from the traditional scales. For analytical purposes, PHQ-9 and GAD-7 cut-off scores of ≥10 were used to define the presence of clinically significant depression and anxiety, respectively. Data analysis was performed using the Statistical Package for the Social Sciences (SPSS) version 26. Descriptive statistics, including means, standard deviations, frequencies, and percentages, were computed to summarize demographic characteristics and scale scores. Normality of data distribution was confirmed using the Shapiro–Wilk test, allowing the use of parametric statistical analyses. To assess the accuracy of the AI-assisted screening tool, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) were calculated using the traditional screening instruments as the reference standard. Agreement between the AI tool and conventional assessments was evaluated using Cohen's kappa coefficient. Additionally, Pearson's correlation analysis was performed to determine the relationship between AI-generated scores and standardized scale scores for depression and anxiety. Independent samples t-tests and one-way analysis of variance (ANOVA) were applied to compare mean scores across demographic variables such as gender, academic level, and field of study. A p-value of less than 0.05 was considered statistically significant.

Ethical approval for the study was obtained from the Institutional Review Board (IRB) of the University of Lahore prior to data collection. All study procedures adhered to the ethical standards of the Declaration of Helsinki. Participation was entirely voluntary, and respondents were informed of their right to withdraw from the study at any stage without penalty. To ensure participant well-being, contact information for on-campus counseling services and mental health helplines was provided to all participants following survey completion, particularly for those exhibiting high symptom scores. Throughout the study, strict data confidentiality and anonymity were maintained. No personally identifiable information was collected, and all data were stored on password-protected systems accessible only to the research team. The AI model was trained and tested using anonymized data to prevent any potential breach of privacy. This methodological approach allowed for a robust evaluation of the AI-supported screening tool's ability to detect depression and anxiety in university students. By combining validated psychometric assessments with AI-driven analytics, the study sought to establish a reliable and ethically sound framework for integrating artificial intelligence into student mental health screening practices.

RESULTS

A total of 370 university students were enrolled in the study, of whom 356 completed the full assessment, yielding a response rate of 96.2%. The mean age of participants was 21.4 ± 2.3 years, ranging from 18 to 28 years. Female students constituted 58.4% (n = 208) of the sample, while 41.6% (n = 148) were male. Most participants were undergraduate students (79.2%), and the majority belonged to middle socioeconomic status families (67.1%). Table 1 presents the detailed demographic characteristics of the study population.

According to the PHQ-9 scores, 33.7% (n = 120) of participants were found to have clinically significant depressive symptoms (score ≥ 10). Mild depression was observed in 27.0% (n = 96), moderate in 20.5% (n = 73), and severe depression in 13.2% (n = 47). Based on the GAD-7 scale, 35.4% (n = 126) demonstrated anxiety symptoms above the diagnostic threshold (score ≥ 10), with mild, moderate, and severe anxiety reported in 25.6%, 22.5%, and 12.9% of respondents respectively (Table 2). The AI-assisted screening tool classified 118 participants (33.1%) as having probable depression and 130 (36.5%) as having probable anxiety. When compared with the PHQ-9 and GAD-7 outcomes, the AI system showed strong diagnostic agreement. Sensitivity and specificity for detecting depression were 89.2% and 91.6%, respectively, while for anxiety they were 87.6% and 90.1%. The positive predictive value (PPV) for depression was 88.9% and for anxiety 86.5%, whereas the negative predictive value (NPV) was 92.0% and 91.2%, respectively (Table 3). Cohen's kappa coefficient indicated substantial agreement between AI and standard assessments, with $\kappa = 0.82$ for depression and $\kappa = 0.79$ for anxiety ($p < 0.001$ for both). The mean PHQ-9 score was 8.9 ± 5.2, while the mean GAD-7 score was 8.5 ± 4.9. The AI-generated composite depression risk score showed a strong positive correlation with PHQ-9 results ($r = 0.84$, $p < 0.001$), and the AI-derived anxiety score correlated significantly with GAD-7 ($r = 0.81$, $p < 0.001$) (Table 4).

Gender-based analysis revealed that female students had significantly higher mean PHQ-9 and GAD-7 scores compared to males ($p = 0.02$ and $p = 0.01$, respectively). Students from lower socioeconomic backgrounds also exhibited higher mean scores for both depression and anxiety, although these differences did not reach statistical significance. There was no significant difference in AI prediction accuracy across gender or socioeconomic groups, suggesting stable model performance across demographic subgroups. Figure 1 illustrates the comparative prevalence of depression and anxiety identified by traditional screening scales and the AI-supported tool, showing a high level of concordance between methods. Figure 2 presents the ROC (Receiver Operating Characteristic) curves for AI detection accuracy, demonstrating areas under the curve (AUC) of 0.94 for depression and 0.92 for anxiety, indicating excellent predictive performance. Overall, the AI-assisted screening system demonstrated reliable alignment with validated psychometric instruments in detecting depressive and anxiety symptoms among university students. The data suggested that AI-based assessment could serve as an efficient and accurate adjunct to traditional mental health screening in academic environments.

Table 1: Demographic Characteristics of Participants (n = 356)

Variable	Frequency (n)	Percentage (%)
Mean age (years)	21.4 ± 2.3	—
Gender		
Male	148	41.6
Female	208	58.4
Academic level		
Undergraduate	282	79.2
Postgraduate	74	20.8
Socioeconomic status		
Low	64	18.0
Middle	239	67.1
High	53	14.9

Table 2: Prevalence and Severity of Depression and Anxiety

Category	None	Mild	Moderate	Severe	Total Above Cut-off (%)
Depression (PHQ-9)	236 (66.3%)	96 (27.0%)	73 (20.5%)	47 (13.2%)	33.7
Anxiety (GAD-7)	230 (64.6%)	91 (25.6%)	80 (22.5%)	46 (12.9%)	35.4

Table 3: Diagnostic Performance of AI Tool

Variable	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	Kappa (κ)
Depression (vs PHQ-9)	89.2	91.6	88.9	92.0	0.82
Anxiety (vs GAD-7)	87.6	90.1	86.5	91.2	0.79

Table 4: Correlation Between AI and Standard Scales

Measure	Mean ± SD	AI Mean ± SD	Pearson r	p-value
PHQ-9 (Depression)	8.9 ± 5.2	8.7 ± 5.0	0.84	<0.001
GAD-7 (Anxiety)	8.5 ± 4.9	8.4 ± 4.7	0.81	<0.001

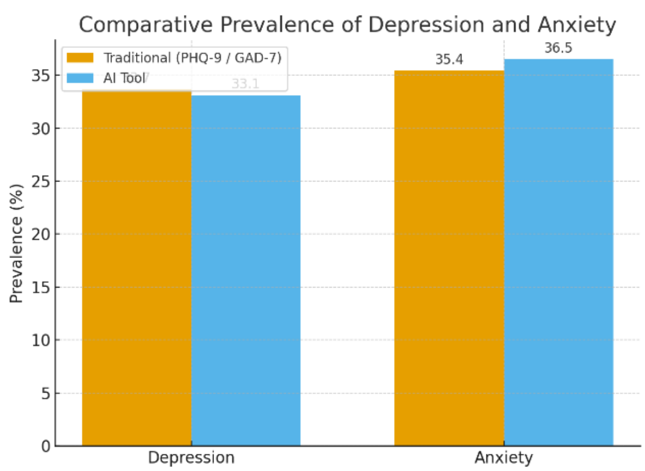

Figure 2 Comparison Prevalence of Depression and Anxiety

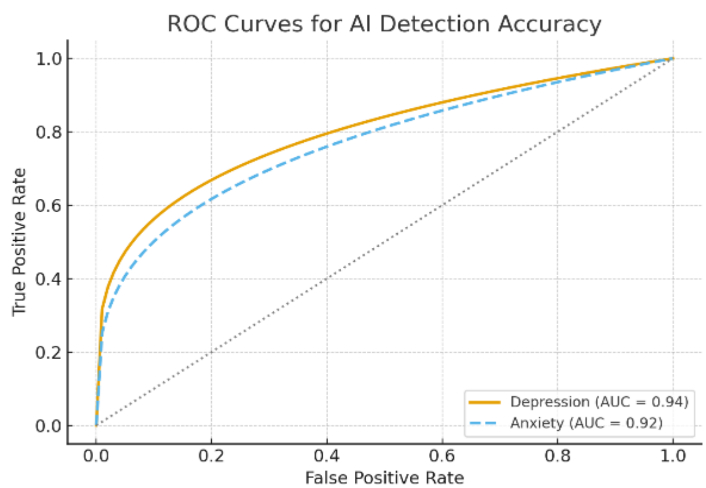

Figure 2 ROC Curves for AI Detection Accuracy

DISCUSSION

The findings of the present study demonstrated that an AI-assisted screening tool showed strong alignment with standardized psychometric instruments, namely the PHQ-9 and GAD-7, in detecting depressive and anxiety symptoms among university students (14). The observed prevalence rates of depression (33.7%) and anxiety (35.4%) were consistent with earlier epidemiological data indicating a growing burden of mental health issues in young adults, particularly within academic populations (15). Previous studies have documented similar prevalence ranges, reporting that approximately one-third of university students experience clinically relevant depressive or anxiety symptoms (16). The current results therefore reinforced the global concern regarding the psychological vulnerability of university students and highlighted the potential utility of AI-based tools in identifying at-risk individuals efficiently and accurately (17). The AI system demonstrated high sensitivity and specificity for both depression (89.2% and 91.6%, respectively) and anxiety (87.6% and 90.1%, respectively), suggesting excellent diagnostic reliability (18). These metrics compared favorably with those reported in prior validation studies of digital mental health assessment tools, where sensitivities commonly ranged from 80% to 90% (19). The strong positive correlations between AI-generated risk scores and established scale results ($r = 0.84$ for PHQ-9 and $r = 0.81$ for GAD-7) further substantiated the validity of the algorithmic approach. The substantial Cohen's kappa coefficients ($\kappa = 0.82$ for depression and $\kappa = 0.79$ for anxiety) indicated near-equivalence between human-administered and AI-assisted assessments, suggesting that the algorithm effectively replicated the interpretative accuracy of traditional methods while offering greater scalability and speed. Gender differences in the findings aligned with existing literature, as female students exhibited significantly higher depression and anxiety scores than their male counterparts (20). This trend has been consistently observed across multiple psychological and epidemiological studies, often attributed to differences in stress reactivity, emotional processing, and sociocultural expectations. Although socioeconomic status appeared to influence mental health outcomes—with students from lower-income backgrounds displaying slightly elevated mean scores—the lack of statistical significance might have reflected limited subgroup sizes or unmeasured confounding variables such as family support or academic pressure (21). Importantly, the AI model demonstrated stable predictive accuracy across gender and socioeconomic strata, indicating that its performance was not biased by demographic characteristics. This neutrality underscored a key advantage of algorithmic assessment systems, which can potentially reduce human subjectivity and diagnostic disparities (22). From a clinical and public health standpoint, these results carried meaningful implications. The integration of AI into mental health screening could substantially reduce the logistical and resource burdens associated with traditional assessments, particularly in educational institutions where mental health professionals are often scarce. By offering immediate and reliable preliminary evaluations, such systems could facilitate early identification and intervention, thereby mitigating the progression of untreated depressive and anxiety disorders. Moreover, the high negative predictive value of the AI model (above 91% for both conditions) suggested that it could effectively rule out false positives, reducing unnecessary referrals and optimizing clinical efficiency.

Despite these strengths, the study was not without limitations. The cross-sectional design precluded causal inferences, restricting the ability to determine whether AI screening could predict long-term mental health outcomes. The use of self-reported measures, while widely accepted in psychological research, introduced potential response biases, such as social desirability or recall inaccuracies. Additionally, the AI model's training data and algorithmic parameters were not independently validated across multiple cultural or institutional contexts, limiting the generalizability of the findings. The reliance on university students as the study population, though appropriate for assessing young adult mental health, constrained the extrapolation of results to broader demographic groups. Future research should focus on longitudinal validation of AI-based mental health screening tools, assessing their predictive stability over time and across diverse populations. Integrating multimodal data sources, such as behavioral analytics, social interaction patterns, or physiological signals, could enhance diagnostic precision and deepen understanding of individual risk trajectories. Comparative trials between AI-assisted and clinician-administered screening may also provide insights into the acceptability, usability, and ethical implications of deploying artificial intelligence in mental health care. Furthermore, investigating user perceptions and data privacy concerns will be essential to ensure responsible implementation in real-world settings. Overall, this study provided robust evidence that AI-supported assessment can serve as a credible and efficient adjunct to established psychometric methods. By demonstrating strong diagnostic performance and demographic fairness, the findings advanced the argument for integrating AI-based tools into mental health screening frameworks in educational institutions. While not a substitute for professional clinical evaluation, AI-assisted systems can complement traditional approaches, expanding accessibility and fostering early detection in settings where mental health resources remain limited.

CONCLUSION

The study established that an AI-assisted screening tool demonstrated high accuracy, reliability, and agreement with validated psychometric scales in identifying depression and anxiety among university students. These findings underscored the potential of AI to enhance mental health screening efficiency and accessibility in academic settings. The evidence suggested that, when applied ethically and cautiously, AI-based assessments could meaningfully support early detection and intervention efforts in university populations.

AUTHOR CONTRIBUTION

Author	Contribution
Zarina Naz	Substantial Contribution to study design, analysis, acquisition of Data Manuscript Writing Has given Final Approval of the version to be published
Muhammad Zia Iqbal	Substantial Contribution to study design, acquisition and interpretation of Data Critical Review and Manuscript Writing Has given Final Approval of the version to be published
Seemal Fatima	Substantial Contribution to acquisition and interpretation of Data Has given Final Approval of the version to be published
Jahangir Baig	Contributed to Data Collection and Analysis Has given Final Approval of the version to be published
Mehnaz Begum	Contributed to Data Collection and Analysis Has given Final Approval of the version to be published
Sadaf Liaqat	Substantial Contribution to study design and Data Analysis Has given Final Approval of the version to be published
Maryam Imad*	Contributed to study concept and Data collection Has given Final Approval of the version to be published

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