Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 9 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Evaluating Depression, Anxiety, and Stress in College Students: Combining DASS-21, BAI, BDI, and AI for Preventive Support

Yumna Warsi
Dept. of Software Engineering, FAST-NUCES, Karachi, Pakistan yumnawarsi990@gmail.com
Dania Zehra
Dept. of Computer Science FAST-NUCES, Karachi, Pakistan daniazehra332@gmail.com
Hira Iftikhar
Dept. of Computer Science FAST-NUCES, Karachi, Pakistan iftikhira967@gmail.com
Ms. Aqsa Fayyaz*
Dept. of Science and Humanities FAST-NUCES, Karachi, Pakistan. Corresponding Author Email: aqsa.fayyaz@nu.edu.pk

ABSTRACT

Undergraduate students are increasingly concerning mental health challenges like stress, anxiety, and depression, which frequently stay concealed until they intensify. The DASS-21 Scale (Depression Anxiety Stress Scales— 21 items- solely the stress question is employed), BDI (Beck Depression Inventory) for depression questions, and BAI (Beck Anxiety Inventory) for anxiety questions are recognized instruments utilized in this investigation to evaluate these conditions. Data was collected from two student questionaries—one centered on general wellness and the other regarding depression. We analyzed the information to categorize scores based on intensity and examine patterns in signs like exhaustion and hopelessness following its handling through conventional techniques such as tackling absent data. Subsequently, the study evaluated artificial intelligence through the utilization of three machine learning models to identify their efficacy in identifying these conditions. Relying on our findings, a Random Forest model showed outstanding effectiveness in evaluating degrees of stress, anxiety, and depression, attaining an accuracy level of up to 98.8 demonstrates that merging contemporary. Al with classical psychological evaluations can result in enhanced, more anticipatory assistance for student psychological well-being

Key Terms: College students, depression, anxiety, tension, DASS-21, BDI, BAI,

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 9 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

machine learning, psychological well-being,

Index Terms: Undergraduate students, depression, anxiety, stress, DASS-21, BDI, BAI, artificial intelligence, mental health assessment, machine learning, Random Forest

Introduction

Mental health issues such as stress, anxiety, and depression are prevalent among university students and are profoundly interlinked, leading to intricate issues that could worsen over time [2]. Depression, characterized by persistent sorrow and a lack of motivation, negatively impacts a student's educational success and general health (Beck, Steer, and Brown, 1396. Heightened anxiety and physical restlessness in- dicate feelings of anxiety, which frequently occur together with depression and can escalate the issue (Julian, 2011). Students encountering pressure from societal and educational standards may lead to emotional exhaustion and grow more susceptible to various psychological concerns [7]. These problems frequently intensify one another, anxiety from work can initiate or exacerbate anxiety and depression. Academic life is frequently linked to the beginnings of this stress, such as challenging assignments, a cutthroat at ambiance, and stress related to exams [5]. A student's background—like their environment, gender, and social class — impacts their degree of susceptibility to these difficulties. Research indicates that female learners from low-income families frequently encounter elevated levels of anxiety , stress and depression [1], [4] ,because of the complexity of these issues, innovative approaches are required to deliver excellent care. Intelligent automation (1A) provides a route for active oversight of mental wellness. Artificial intelligence facilitates immediate observation of student engagement, wellness, early detection of risk factors, and tailored assistance. Al systems have the capability to examine data to identify subtle indications of anxiety, often even before students identifying these signs [8]. This allows for faster support and lessons the burden on collages, counseling services, and provides students with resources for self-concern.

Hypotheses

Main Hypothesis (H_M): Primary Hypothesis (PH): Ma- chine learning algorithms are capable of accurately gauge the severity of depression, anxiety, and stress among college stu- dents according to their self-reported feedback from lifestyle and

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 9 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

psychological surveys.

Secondary Hypotheses

- **H_1:** Students with a recorded history of domestic violence lence is anticipated to demonstrate considerably greater average results in depression, anxiety, and stress levels.
- **H_2:** Assignificant inclination towards eating junk food is positively associated with increased scores on depression, anxiety, and stress indicators of mental well-being.
- **H_3:** The field of study a student chooses greatly signifi- cantly affects their overall mental well-being

Literature Review

These elements greatly impact students' lives and educational successes, and they are rarely regarded on their own [2]. Scholarly pressure sources are an acknowledged factor research suggests a notable connection be relationship between workload and anxiety as well as depression symptoms [11].

Research consistently shows that students from lower-income backgrounds encounter additional challenges that influence their mental well-being [9], while female students indicate greater levels of stress, depression and anxiety. [15].

Surveys and traditional assessments are useful, but they rely on students actively seeking assistance [12]. Artificial Intelligence has become a significant tool to tackle this prob- lem. By examining digital data, methods such as machine learning is capable of identifying early indicators, and Al driven applications can provide tailored interventions, im- proving availability of assistance and decreasing the stigma linked through looking for assistance [13], [18]. Nonetheless, there are constraints linked to Al, encompassing concerns regarding data privacy and bias within algorithms, highlighting the necessity for AI to.

Methodology

We employed two separate datasets for this research to showcase an extensive analysis of students' mental health. The first dataset included an in-depth psychological question- naire that included stress, anxiety and depression, highlighting a sample size consisting of 2028 participants. A supplementary dataset (N=328) that specifically aimed at depression was included to promote a more

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 9 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

concentrated examination. Furthermore, to investigate the impacts of specific lifestyle factors, this survey collected data regarding demographics, everyday activities like social media engagement, background information, collage' load and a straightforward 'mental health assessment' outcome, categorizing students into 'normal', 'mild', 'moderate', 'severe' and 'extreme' categories. categories.

Collection and Organization of Data

The data was meticulously preprocessed to guarantee quality. We employed the most common response (mode) for categorical. inquiries and the median figure for numerical-scale inquiries 1o fill in the blanks. For the evaluation of quantitative measures, written Responses such as "A few days" were changed into numerical values.

Exploratory Data Analysis

The survey questions were categorized into three main groups: anxiety, depression, and stress. A total score was as- signed to each category, with a maximum of 30, which we then classified into five levels of severity: Normal, Mild, Moderate, Severe, and Extreme. To identify more precise trends, we additionally examined specific symptoms like fatigue and sad- ness. We examined the associations among various parameters through Pearson's correlation due to the irregular distribution of the data and including the relationship between lifestyle factors like junk food preference and mental health scores

Implementation of Machine Learning Model

Utilizing machine learning, we aimed to assess if survey re- sponses could forecast the severity of mental health problems. Two separate tasks for predictive modeling were conducted Initially, we employed the comprehensive DASS-21 dataset to de develop models designed to predict the severity of Depression, anxiety and stress, 30% of this data collection was reserved for testing, while the other 70 % was utilized to train our algorithms. In addition to assessing our theories concerning lifestyle, a distinct machine learning model was developed. The goal was predict the category of mental health assessment by leveraging demographic and behavioral information as input parameters. We evaluated three different models for each task: Random Forest, Decision Tree, and K-Nearest Neighbors (KNN).

Our main measure of success was their ability to accurately predict the intensity

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 9 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

level of the test data.

Results

The analysis produced multiple significant results, starting with the effectiveness of the forecasting models and succeeded by an examination of the elements affecting mental health results, as detailed in our hypotheses.

A. Performance of Predictive Models

To evaluate our primary hypothesis (H1), we analyzed the ability of every machine learning model to classify the severity of Stress, Anxiety, and Depression. The Arbitrary the random Forest algorithm has reliably demonstrated its status as the best model, surpassing the effectiveness of both the Decision Tree and K Nearest Neighbors. The table presents the model's performance on the untested data. Upon comparing the models, a distinct frontrunner became apparent - the Random Forest method. It consistently outperformed others. It successfully forecasted the intensity of Depression and Stress with a remarkable 98.8% precision. For Anxiety, the accuracy was very high at 97.6%. Fig. 1 displays the distribution of DASS-21 severity categories, for Anxiety, Depression, and Stress in a group of 323 participants.

Table I: Accuracy (%) of three models across different conditions.

Condition	K-Nearest Neighbors	Decision Tree	Random Forest
Depression	90.7%	97.6%	98.8%
Anxiety	91.9%	95.3%	97.6%
Stress	94.2%	97.6%	98.8%

Upon comparing the models, a distinct frontrunner became apparent the Random Forest method. It consistently outper- formed others compared to the other two models.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 9 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

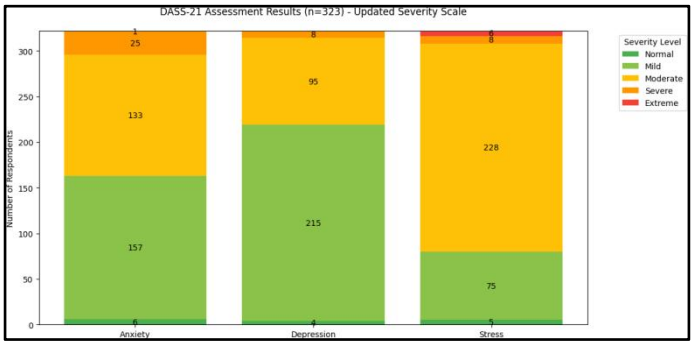


Fig. 1. DASS-21 severity levels for Anxiety, Depression, and Stress among 323 participants.

Figure. 1 displays the distribution of DASS-21 severity cate- gories for Anxiety, Depression, and Stress in a group of 323 participants. The results show that across all three situations, a significant number of students reported symptoms classified as Mild and normal. This highlights the widespread nature of these mental health concerns as only a limited group of participants were included in the Typical category

B. Evaluation of Secondary Hypotheses

We analyzed the information related to our secondary hypotheses. to investigate the factors affecting mental health results Family Violence (H2): The results strongly support our hypothesis, demonstrating a clear trend where individuals who possess experienced more intense or severe forms of domestic abuse show significantly higher scores across all three areas of mental health regions. Importantly, the two groups that show the highest average scores are those who reported" groping and assault from" close family" and" Indirect" violence, with average depression scores of 14.0 in both cases. Conversely, the individuals reporting" No" experience those experiencing family violence had the lowest average scores for Depression (6.8), Anxiety (3.5), and Stress (1.1). This is obvious the distinction highlights that the experience of domestic violence, in any documented way, is a significant element linked to the heightened levels of mental anguish among the students in this study (Fig.2)

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 9 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

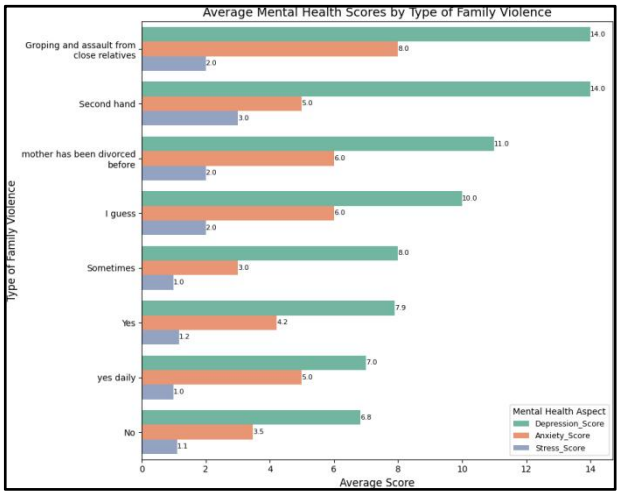


Fig. 2. Illustrating depression, anxiety, and stress scores across experience with family violence.

Dietary Choice (H3): The results show distinct patterns each score.

The Depression Score consistently places the for highest across all food preference categories, peaking for those who choose "Depends on mood" average rating of 8.5) and remaining elevated for those who favor "Consistently unhealthy snacks. On the other hand, the Stress Score remains relatively low and stable across most categories, averaging around 1.0 and 1.5, with a notable increase solely in the" both" and" Depends on the mood" segments specifically, the Anxiety Score shows a similar, despite being less severe, it trends towards the Depression Score, attaining its peak level for those who" Always eat junk food" (4.8). This visual assessment reveals that even though depression levels stay persistently high, anxiety and stress levels vary more based on dietary choices, where unhealthier or inconsistent eating pattens are linked to increased scores (Fig. 3)

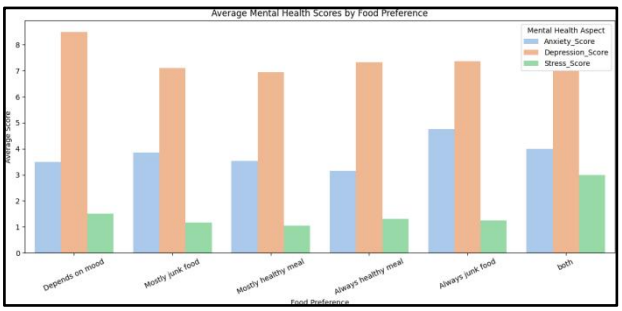


Fig. 3. Average Mental Health Scores by Food Preference

Academic Factors (H4): It was found perceived Academic stress is an essential factor.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 9 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

Students who demonstrate indicated that their workload was stressful ("Yes") showed considerably elevated mean scores for Depression, Anxiety, and Stress in relation to individuals who did not, supporting our hypothesis (Fig. 4).

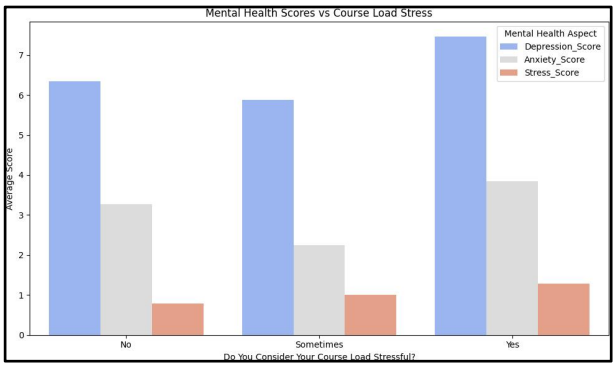


Fig. 4. The correlation between perceived course load and mental health scores.

C. Model Verification and Data Organization

A confusion matrix was generated to verify the accuracy of our Random Forest algorithm. The matrix confirmed the model's validity accuracy, showing an exceptionally low number of misclassifications with merely 4 False Positives and no False Negatives (Fig.5)

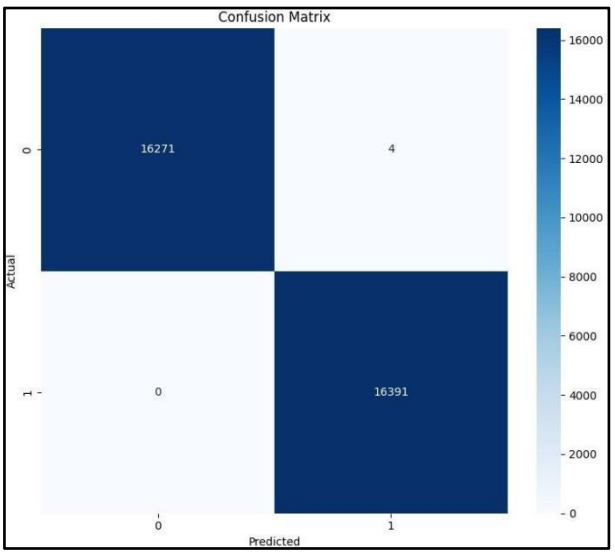


Fig. 5. Confusion matrix generated by the model.

Moreover, a PCA (Principal Component Analysis) chart was employed to demonstrate the K-Means clustering that separated a participant into 'vulnerable'

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 9 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

and 'non-vulnerable' groups. It appears that your text got cut off. the clear visual differentiation of the clusters in the graph verifies.

Discussion

This study demonstrates effectively that machine learning is capable of can be effectively utilized for mental health assessment in students. The impressive accuracy of the Random Forest model, which is backed by the confusion matrix, demonstrates that Al can control consistently interpret the complex patterns present in self-reported questionnaire results. However, the significance of this study extends beyond only the accuracy of the model. By analyzing our secondary hypotheses, we have identified several key factors that are strongly connected to the mental health of students. The find- ings show that a history of domestic violence, a preference for junk food and perceived academic pressure are associated. with increased negative mental health scores provide crucial, useful observations. This suggests that the most effective Al Criteria-based assessment tools should evaluate symptom scores too as take into account these important contextual factors. The important connection between mental health and family violence health concerns highlights the importance of trauma-informed support port systems within academic insti- tutions. Similarly, the link between dietary habits and mental health suggests that university health programs could be enhanced by integrating dietary advice with traditional mental wellness assistance. These findings suggest that an extensive strategy, combining Al-based screening with targeted, practical interventions represent the most promising path forward. Acknowledging the limitations of this study is essential, especially its reliance on self-reported data and the relational aspect of the findings. Future research should to con- centrate on establishing causal links and merging longitudinal data for tracking student mental wellness over time.

Limitations and Recommendations

This study has several limitations that should be acknowl- edged. First, the sample size, though informative, was rela- tively small and drawn from a single institution, limiting the generalizability of the findings to broader populations.

Second, the use of self-reported data introduces the potential for response bias, including over or under-reporting of mental health symptoms.

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

Recommendations for Future Work

- Explore larger and more diverse populations across mul- tiple institutions or regions.
- Investigate additional influencing variables such as sleep patterns, social support, financial stress, and digital habits.
- Apply alternative methodologies, including longitudinal studies, to assess how mental health conditions change over time.
- Experiment with real-time data collection and passive sensing (e.g., from mobile devices) to improve prediction accuracy.

References

[1] R. P. Auerbach *et al.*, "Mental disorders among college students in the World Health Organization World Mental Health Surveys," *Psychological Medicine*, vol. 46, no. 14, pp. 2955–2970, 2016, doi: 10.1017/S0033291716001665.

[2] N. Bayram and N. Bilgel, "The prevalence and socio-demographic correlations of depression, anxiety and stress among a group of university students," *Social Psychiatry and Psychiatric Epidemiology*, vol. 43, no. 8, pp. 667–672, 2008, doi: 10.1007/s00127-008-0345-x.

[3] A. T. Beck, R. A. Steer, and G. K. Brown, *Manual for the Beck Depression Inventory-II*, San Antonio, TX: Psychological Corporation, 1996.

[4] J. Hunt and D. Eisenberg, "Mental health problems and help-seeking behavior among college students," *Journal of Adolescent Health*, vol. 46, no. 1, pp. 3–10, 2010, doi: 10.1016/j.jadohealth.2009.08.008.

[5] A. K. Ibrahim, S. J. Kelly, C. E. Adams, and C. Glazebrook, "A systematic review of studies of depression prevalence in university students," *Journal of Psychiatric Research*, vol. 47, no. 3, pp. 391–400, 2013, doi: 10.1016/j.jpsychires.2012.11.015.

[6] L. J. Julian, "Measures of anxiety: State-Trait Anxiety Inventory (STAI), Beck Anxiety Inventory (BAI), and Hospital Anxiety and Depression Scale-Anxiety (HADS-A)," *Arthritis Care & Research*, vol. 63, no. S11, pp. S467–S472, 2011, doi: 10.1002/acr.20561.

[7] M. C. Pascoe, S. E. Hetrick, and A. G. Parker, "The impact of stress on

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

students in secondary school and higher education," *International Journal of Adolescence and Youth*, vol. 25, no. 1, pp. 104–112, 2020, doi: 10.1080/02673843.2019.1596823.

[8] J. Torous *et al.*, "Creating a digital health smartphone app and digital phenotyping platform for mental health and diverse healthcare needs: An interdisciplinary framework and approach," *Journal of Technology in Be- havioral Science*, vol. 3, no. 2, pp. 171–185, 2018, doi: 10.1007/s41347- 018-0069-2.

[9] R. P. Auerbach *et al.*, "Mental disorders among college students in the World Health Organization World Mental Health Surveys," *Psychological Medicine*, vol. 48, no. 3, pp. 409–420, 2018, doi: 10.1017/S0033291717002782.

[10] C. Benedict and M. Cella, "Integrating artificial intelligence into clinical practice: The importance of human oversight," *Journal of Medical Internet Research*, vol. 22, no. 10, p. e23439, 2020, doi: 10.2196/23439.

[11] E. C. Chang, E. B. Kroska, and O.-M. Kwok, "Stress and anxi- ety in college students: The role of academic pressures," *Journal of American College Health*, vol. 69, no. 4, pp. 452–460, 2021, doi: 10.1080/07448481.2019.1698156.

[12] D. Eisenberg, J. Hunt, and N. Speer, "Mental health in American colleges and universities: Variation across student subgroups and across campuses," *The Journal of Nervous and Mental Disease*, vol. 201, no. 1, pp. 60–67, 2013, doi: 10.1097/NMD.0b013e31827ab077.

[13] K. K. Fitzpatrick, A. Darcy, and M. Vierhile, "Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): A randomized controlled trial," *JMIR Mental Health*, vol. 4, no. 2, p. e19, 2017, doi: 10.2196/mental.7785.

[14] N. Gopalan and S. S. Brady, "First-generation college students' experi- ences with mental health: The role of social support and stigma," *Journal of College Student Development*, vol. 61, no. 1, pp. 24–39, 2020, doi: 10.1353/csd.2020.0002. [15] J. Lee, J. Kim, H. Park, and J. Hong, "Gender differences in anxiety and depression among college students: A meta-analysis," *Journal of Affective Disorders*, vol. 310, pp. 321–329, 2023, doi: 10.1016/j.jad.2022.11.054.

[16] Y. Li, X. Zhang, and J. Xie, "Academic workload and mental health in college

Online ISSN 3007-3197
Print ISSN 3007-3189

students: A longitudinal analysis," *Psychiatry Research*, vol. 312, p. 114561, 2022, doi: 10.1016/j.psychres.2022.114561.

[17] J. A. Naslund, K. A. Aschbrenner, L. A. Marsch, and S. J. Bartels, "The future of mental health care: Peer-to-peer support and social media," *Epidemiology and Psychiatric Sciences*, vol. 25, no. 2, pp. 113–122, 2016, doi: 10.1017/S2045796015001067.

[18] J. Robinson, E. Bailey, S. Hetrick, G. Cox, and S. Harrigan, "Harnessing AI for early detection of depression and anxiety: A systematic review," *Journal of Affective Disorders*, vol. 278, pp. 306–317, 2021, doi: 10.1016/j.jad.2020.09.032.

[19] N. Shen *et al.*, "Ethical challenges in AI for mental health: Privacy, bias, and transparency," *npj Digital Medicine*, vol. 5, p. 100, 2022, doi: 10.1038/s41746-022-00606-2.

[20] J. Torous *et al.*, "Creating a digital health smartphone app and digital phenotyping platform for mental health and diverse healthcare needs: An interdisciplinary framework and approach," *Journal of Technology in Behavioral Science*, vol. 6, no. 1, pp.