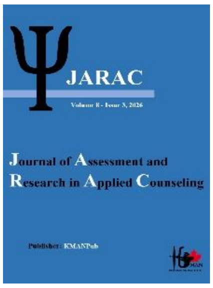
KMAN PUBLISHING INSTITUTE
Journal Website

Article history:
Received 05 March 2026
Revised 22 May 2026
Accepted 10 June 2026
Initial Publish 25 June 2026
Published online 01 July 2026

Journal of Assessment and Research in Applied Counseling

Volume 8, Issue 3, pp 1-14



E-ISSN: 3041-8518

Explainable XGBoost Models for Predicting Generalized Anxiety Disorder from Digital Mental Health Indicators

Airton. Knaul[1], Citieli. Giongo[1*]

[1] Department of Psychology, University of Western Ontario, London, ON N6A 3K7, Canada

*** Corresponding author email address**: citieli-giongo@alliant.edu

A r t i c l e   I n f o

Article type:
Original Research

How to cite this article:
Knaul, A., & Giongo, G. (2026). Explainable XGBoost Models for Predicting Generalized Anxiety Disorder from Digital Mental Health Indicators. *Journal of Assessment and Research in Applied Counseling*, *8*(3), 1-14.
http://dx.doi.org/10.61838/kman.jarac.2340

A B S T R A C T

Objective: This study aimed to develop and evaluate an explainable XGBoost model for predicting generalized anxiety disorder from psychological, behavioral, and digital mental health indicators among Canadian adults.

Methods and Materials: This cross-sectional predictive study was conducted with 2,412 adults from Canada. Data were collected using standardized measures of generalized anxiety, psychological distress, depressive symptoms, sleep quality, smartphone addiction, and social media addiction, along with a structured digital lifestyle questionnaire assessing daily screen time, sleep duration, physical activity, technology-related stress, digital notification frequency, remote work hours, online gaming, and demographic characteristics. Generalized anxiety disorder risk was classified using the GAD-7 clinical cut-off. After preprocessing, missing-data imputation, feature encoding, and feature engineering, the dataset was divided into stratified training and testing subsets. An XGBoost classification model was optimized through cross-validation, and model explainability was examined using SHapley Additive exPlanations.

Findings: Generalized anxiety symptoms were strongly correlated with psychological distress ($r = .79$, $p < .01$) and depressive symptoms ($r = .74$, $p < .01$), and moderately to strongly correlated with poor sleep quality ($r = .61$, $p < .01$), smartphone addiction ($r = .54$, $p < .01$), and social media addiction ($r = .46$, $p < .01$). The optimized XGBoost model showed excellent predictive performance on the independent test set, with accuracy of 91.8%, precision of 89.6%, recall of 88.2%, specificity of 93.5%, F1-score of 88.9%, ROC-AUC of .957, PR-AUC of .944, balanced accuracy of 90.9%, Matthews correlation coefficient of .819, and Brier score of .081. SHAP analysis identified psychological distress, depression, sleep quality, smartphone addiction, previous mental health diagnosis, screen time, social media addiction, and technology-related stress as the most influential predictors.

Conclusion: Explainable XGBoost modeling demonstrated high accuracy and interpretability for predicting generalized anxiety disorder from digital mental

health indicators, supporting its potential use in early screening, risk stratification, and personalized digital mental health assessment.
Keywords: *Generalized anxiety disorder; XGBoost; explainable artificial intelligence; SHAP; digital mental health; digital phenotyping; smartphone use.*

1. Introduction

Generalized anxiety disorder is one of the most clinically and socially consequential forms of internalizing psychopathology because it is characterized by persistent worry, heightened physiological arousal, cognitive anticipation of threat, impaired concentration, sleep disruption, and difficulty regulating uncertainty in everyday life. Although anxiety symptoms are traditionally assessed through clinical interviews and standardized self-report questionnaires, contemporary mental health research increasingly recognizes that anxiety is not expressed only through subjective symptoms but also through daily behavioral patterns, sleep-wake rhythms, mobility, social communication, digital media use, and real-time fluctuations in affective and cognitive functioning. This recognition has become especially important in the context of digital mental health, where smartphones, wearable devices, ecological momentary assessment, passive sensing, and artificial intelligence offer new opportunities to identify psychological risk outside conventional clinical settings. Instead of depending exclusively on retrospective symptom reports, digital mental health indicators make it possible to examine how anxiety-related processes unfold in naturalistic contexts, including changes in screen activity, sleep regularity, physical activity, social interaction, digital communication, and technology-related stress. The emergence of digital phenotyping has therefore shifted mental health assessment from a static and clinic-centered model toward a more dynamic, continuous, and ecologically valid framework for understanding emotional disorders (Maatoug et al., 2022; Mendes et al., 2022; Moukaddam et al., 2022).

Digital phenotyping refers to the use of data generated through smartphones, wearable sensors, online platforms, and other digital systems to characterize behavioral, physiological, and psychological patterns relevant to mental health. Conceptual and methodological reviews have emphasized that digital phenotypes can capture both active data, such as self-reported mood ratings and ecological momentary assessment responses, and passive data, such as sleep, movement, typing, location, device interaction, and communication patterns (Breitinger et al., 2023; Bufano et al., 2023; Maatoug et al., 2022). In mood and internalizing disorders, digital phenotyping is particularly valuable because symptoms fluctuate across time, context, and interpersonal environments, making single-time-point assessments insufficient for capturing the complexity of psychological distress. Recent work has also highlighted the growing relevance of digital biomarkers for diagnosis, treatment monitoring, and relapse prediction in mood disorders, suggesting that digital indicators can complement conventional clinical assessments by providing objective and temporally sensitive information (Garzón-Partida et al., 2025). Similarly, the increasing attention given to passive sensing as a behavioral marker of psychopathology shows that daily digital traces may provide clinically meaningful information about functional impairment, emotional regulation, sleep disturbance, and vulnerability to symptom escalation (Fulford & Jacobson, 2025). These developments suggest that generalized anxiety disorder may be more accurately understood when psychological symptoms are analyzed together with digitally observable indicators of daily functioning.

The expansion of smartphone-based and wearable-based mental health assessment has created a strong empirical foundation for predictive modeling of anxiety and related conditions. Smartphone-derived biobehavioral rhythms have been associated with depression, anxiety, and sleep disturbance, indicating that routine patterns extracted from mobile devices may reflect underlying emotional dysregulation and behavioral instability (Winbush et al., 2026). Systematic reviews of active and passive ambulatory assessment in bipolar disorder have similarly shown that mobile mood monitoring and passive sensing measures can provide useful information about affective variability and symptom trajectories, even though methodological heterogeneity remains a central challenge for the field (Wright et al., 2026). In depression and anxiety research, observational protocols using smartphone and wearable-based digital phenotyping have been developed to support real-time screening and prediction, showing that integrated digital systems can be used to capture symptoms, behavioral routines, sleep, and activity in ecologically valid settings (Shin et al., 2025). Protocols for real-time monitoring of depressive symptoms also demonstrate the increasing feasibility of using digital data streams to predict emotional states before they become clinically severe (Lee & Lee, 2025). Together, these studies show that digital technologies are not merely tools for remote data collection but are becoming central instruments for constructing predictive models of mental health risk.

Sleep and circadian functioning are especially relevant for predicting generalized anxiety disorder because anxiety is closely connected to hyperarousal, difficulty initiating sleep, nocturnal worry, and daytime fatigue. Digital methods now allow sleep to be estimated through smartphone and wearable sensors, enabling researchers to examine sleep duration, sleep timing, and sleep regularity without relying exclusively on retrospective self-report. Recent work on sleep estimation from low-frequency smartphone sensors has demonstrated the potential of Bayesian modeling approaches for extracting sleep-related information from passive device data (Byun et al., 2025). Smartphone-derived rhythms also provide information about sleep-wake regularity and behavioral timing, which may be directly relevant to anxiety and emotional dysregulation (Winbush et al., 2026). Consumer-grade wearable devices have been reviewed as potentially useful tools for inferring physical and mental health outcomes in severe mental illness, especially when interpreted cautiously and integrated with clinical information (Hassan et al., 2025). These findings are important because generalized anxiety disorder is frequently accompanied by disrupted sleep, reduced recovery, and altered daily rhythms. Therefore, digital sleep and activity indicators may strengthen prediction models by adding behavioral and physiological information that cannot be fully captured through symptom questionnaires alone.

Smartphone use, social media engagement, and broader digital media behaviors have also become important variables in mental health research. Problematic smartphone use can intensify stress, sleep disturbance, attentional fragmentation, and compulsive checking behaviors, all of which may interact with worry and anxiety symptoms. Ecological momentary assessment studies of problematic smartphone use during examination weeks have shown that app-based approaches can capture dynamic changes in digital behavior and psychological states during periods of elevated stress (Ahn et al., 2025). Research on digital media use in young adults has further suggested that the process of self-reporting and wearable data collection itself may influence behavioral awareness and produce unintended positive behavioral changes, demonstrating that digital monitoring is not always passive but can also alter self-regulation (Jo et al., 2025). Social media exposure represents another major component of the digital mental health environment. Evidence from research on social media detox and youth mental health suggests that modifying social media engagement may influence psychological outcomes, highlighting the clinical significance of digitally mediated social behavior (Calvert et al., 2025). Umbrella reviews of mobile assessments for monitoring youth mental health further emphasize that smartphone-based measures are increasingly used to understand how affective symptoms, social behavior, and digital environments interact across developmental contexts (Marciano et al., 2023a, 2023b). These lines of research indicate that digital media indicators should be considered not only as behavioral covariates but also as potential predictors of anxiety risk.

Digital phenotyping has been applied across a wide range of clinical and health contexts, demonstrating its relevance beyond a single diagnostic category. In schizophrenia research, the integration of cognitive, functional, and digital phenotyping assessments has been proposed as a pathway toward identifying clinically meaningful subtypes, suggesting that digital variables may help refine psychiatric classification and individualized care (Byun et al., 2024). In obsessive-compulsive disorder, scoping reviews of wearable and mobile technologies have shown that digital tools can support evaluation and treatment monitoring by capturing behavioral patterns that may otherwise remain invisible in standard assessments (Frank et al., 2023). Digital phenotyping protocols for patients with cancer have also been designed to monitor disease trajectories and psychological functioning, showing that mobile and sensor-based indicators can be applied in complex medical populations where emotional symptoms fluctuate alongside physical health demands (Jenciūtė et al., 2023). Similarly, digital home monitoring studies in long COVID have illustrated how repeated measures can capture daily symptom fluctuation in real-world environments, reinforcing the value of longitudinal and high-frequency digital data for health prediction (Mansoubi et al., 2023). These studies collectively suggest that digital phenotyping is not restricted to psychiatric symptom measurement but represents a broad methodological approach for understanding variability, functioning, and risk across health conditions.

Despite these advances, the use of digital mental health indicators for predicting generalized anxiety disorder remains less developed than research on depression, bipolar disorder, or severe mental illness. Much of the empirical literature has focused on depression, mood disorders, or general psychological distress, while anxiety-specific prediction models require further development. Systematic reviews examining the digital footprint of depression have shown that digital traces can reflect affective and behavioral features of depressive states, including reduced activity, altered communication, and changes in online behavior (Zarate et al., 2022). However, anxiety may present a different digital signature because it is often characterized by heightened checking, excessive information seeking, sleep disruption, avoidance, increased sensitivity to notifications, and persistent anticipatory worry. At the same time, digital interventions for anxiety and depression have advanced rapidly. Digital positive affect interventions have been tested as treatment approaches for anxiety and depression, demonstrating the growing integration of technology into emotional disorder care (Zainal et al., 2025). AI-driven just-in-time adaptive intervention mechanisms have also been proposed for preventing anxiety and depressive disorders through app-based systems that respond to real-time risk states (Zarski et al., 2025). These developments point to a critical need for predictive models that can identify anxiety risk accurately and explainably before symptoms become more severe.

Machine learning offers a powerful framework for analyzing complex, nonlinear, and high-dimensional relationships among psychological symptoms, digital behaviors, and demographic characteristics. Binary classification models have already been emphasized as important tools for predicting depression from a machine learning perspective, particularly because they allow researchers to distinguish individuals at elevated risk from those at lower risk using multiple interacting predictors (Choudhary & Srinivasan, 2022). More recent discussions of small-data machine learning and personalized digital phenotyping have argued that computational models can contribute to precision psychiatry by generating individualized forecasts from behavioral and psychological data, even when datasets are not extremely large (Wang et al., 2025). Artificial intelligence combined with smartphone technology has also been proposed as a means of enhancing personalized assessment and treatment in mental health conditions, including eating disorders, where individualized behavioral signals may inform intervention decisions (Linardon & Torous, 2025). For generalized anxiety disorder, machine learning is especially promising because anxiety symptoms are influenced by interacting factors such as psychological distress, depressive symptoms, sleep quality, screen time, social media use, physical activity, previous diagnosis, and technology-related stress. Traditional regression models can estimate linear associations among these variables, but machine learning models such as XGBoost can better capture nonlinear thresholds, interactions, and complex feature dependencies.

Among machine learning methods, Extreme Gradient Boosting is particularly suitable for predictive modeling in digital mental health because it can handle structured clinical and behavioral data, model nonlinear relationships, rank variable importance, and maintain strong predictive performance even when predictors vary in scale and distribution. However, the increasing use of machine learning in mental health also raises concerns regarding interpretability, clinical trust, fairness, and practical implementation. A model that predicts generalized anxiety disorder accurately but cannot explain why a participant is classified as high risk has limited value for clinicians, researchers, and public health systems. Explainable artificial intelligence addresses this limitation by providing interpretable estimates of how each predictor contributes to both global model behavior and individual predictions. This is especially important in digital mental health, where predictors may include sensitive behavioral information such as screen time, social media engagement, sleep disruption, and digital communication patterns. Explainability allows researchers to determine whether the model is relying primarily on clinically plausible features, such as psychological distress and sleep quality, or on potentially biased or unstable demographic indicators. The protocols developed for wearable and ecological momentary assessment predictors of non-response to cognitive behavioral therapy for internalizing disorders illustrate the growing importance of using digital indicators not only for prediction but also for clinically meaningful interpretation (Hammelrath et al., 2025a, 2025b). In this context, explainable XGBoost modeling may provide a methodologically rigorous and clinically interpretable approach for identifying generalized anxiety disorder from digital mental health indicators.

The present study is positioned at the intersection of digital phenotyping, predictive psychiatry, and explainable artificial intelligence. It responds to the need for anxiety-specific predictive models that integrate conventional psychological measures with digital lifestyle variables, including smartphone addiction, social media addiction, daily screen time, sleep quality, sleep duration, physical activity, technology-related stress, notification frequency, remote work exposure, and other digitally mediated behavioral indicators. By focusing on generalized anxiety disorder in a Canadian adult sample, the study contributes to the development of contextually relevant digital mental

JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518

health screening models that may support early detection, risk stratification, and personalized prevention. The use of explainable XGBoost is important because it allows the model to move beyond simple classification accuracy and provide interpretable evidence regarding which digital and psychological indicators most strongly influence anxiety prediction. The aim of this study was to develop and evaluate an explainable XGBoost model for predicting generalized anxiety disorder from digital mental health indicators and to identify the most influential psychological, behavioral, and technology-related predictors contributing to model decisions.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a cross-sectional, predictive machine learning design to develop and validate an explainable Extreme Gradient Boosting (XGBoost) model for predicting the presence of Generalized Anxiety Disorder (GAD) using a comprehensive set of digital mental health indicators. The research was conducted across five Canadian provinces, including Ontario, British Columbia, Alberta, Quebec, and Nova Scotia, between January and October 2025. Participants were recruited through university mailing lists, digital mental health platforms, online community advertisements, and social media campaigns. Eligibility criteria included being at least 18 years of age, residing in Canada, possessing sufficient English proficiency to complete the questionnaires, and reporting regular use of digital devices such as smartphones, tablets, or computers. Individuals with severe neurological disorders, cognitive impairments, or incomplete survey responses exceeding 10% of the questionnaire items were excluded from the study. A total of 2,648 participants initially consented to participate. After removing duplicate submissions, incomplete questionnaires, and cases failing quality-control procedures such as attention-check items and response-time screening, data from 2,412 participants were retained for the final analyses. The final sample consisted of 1,376 women (57.0%), 1,006 men (41.7%), and 30 participants (1.3%) identifying as non-binary or another gender identity. Participants ranged in age from 18 to 69 years, with a mean age of 34.82 years (SD = 11.26).

2.2. Measures

Digital mental health indicators were assessed using a combination of standardized psychological instruments and technology-related behavioral measures. Generalized anxiety symptoms were evaluated using the Generalized Anxiety Disorder-7 (GAD-7), developed by Spitzer, Kroenke, Williams, and Löwe in 2006. The GAD-7 consists of seven items measuring the frequency of anxiety symptoms experienced during the previous two weeks. Responses are rated on a four-point Likert scale ranging from 0 (not at all) to 3 (nearly every day), yielding total scores between 0 and 21, with higher scores reflecting greater anxiety severity. The instrument has consistently demonstrated excellent psychometric properties across community and clinical populations, with Cronbach's alpha values typically exceeding .90 and strong construct, convergent, and criterion validity.

Psychological distress was measured using the Kessler Psychological Distress Scale (K10), originally developed by Kessler and colleagues in 2002. The K10 comprises ten items assessing symptoms of anxiety and depression experienced during the preceding four weeks. Each item is rated on a five-point Likert scale ranging from 1 (none of the time) to 5 (all of the time), producing total scores from 10 to 50. Higher scores indicate greater levels of nonspecific psychological distress. Previous research has consistently supported the instrument's internal consistency, factorial validity, and diagnostic utility for identifying individuals experiencing clinically significant emotional distress.

Depressive symptoms were assessed using the Patient Health Questionnaire-9 (PHQ-9), developed by Kroenke, Spitzer, and Williams in 2001. This nine-item instrument evaluates the frequency of depressive symptoms during the previous two weeks using a four-point response scale ranging from 0 (not at all) to 3 (nearly every day). Total scores range from 0 to 27, with higher scores indicating more severe depressive symptomatology. The PHQ-9 has demonstrated excellent reliability and validity across numerous international studies and has become one of the most widely used screening tools for depression in both clinical practice and epidemiological research.

Sleep quality was evaluated using the Pittsburgh Sleep Quality Index (PSQI), developed by Buysse and colleagues in 1989. The PSQI contains 19 self-report items that generate seven component scores assessing subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. Component scores are summed to obtain a global score ranging from 0 to 21, with higher scores representing poorer sleep quality. Extensive psychometric evaluations have confirmed the reliability, validity, and sensitivity of the PSQI in diverse adult populations.

Problematic smartphone use was measured using the Smartphone Addiction Scale–Short Version (SAS-SV), developed by Kwon and colleagues in 2013. The scale contains ten items rated on a six-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree). Higher total scores indicate greater levels of problematic smartphone use and behavioral dependence on mobile devices. Previous investigations have consistently demonstrated high internal consistency, satisfactory construct validity, and strong concurrent validity across adolescent and adult populations.

Social media engagement was assessed using the Bergen Social Media Addiction Scale (BSMAS), developed by Andreassen and colleagues in 2016. The instrument consists of six items evaluating salience, mood modification, tolerance, withdrawal, conflict, and relapse associated with social media use. Responses are recorded on a five-point Likert scale ranging from 1 (very rarely) to 5 (very often), with higher scores reflecting more problematic patterns of social media engagement. The BSMAS has demonstrated strong psychometric performance across numerous cultural settings.

Digital behavior variables were additionally collected through a structured Digital Lifestyle Questionnaire specifically developed for this study based on previous digital health surveillance frameworks. The questionnaire collected information regarding average daily smartphone screen time, total internet usage, frequency of social media engagement, number of digital notifications received, average daily physical activity tracked through wearable devices or smartphone applications, sleep duration estimated from digital health applications, remote working hours, online gaming frequency, digital communication patterns, and self-reported technology-related stress. Sociodemographic variables including age, gender, educational attainment, employment status, marital status, annual household income, province of residence, and history of previous mental health diagnosis were also collected to enhance predictive performance and facilitate adjustment for potential confounding factors. Prior to model development, all continuous variables were standardized where appropriate, categorical variables were encoded using one-hot encoding, missing values below 5% were imputed using multiple imputation procedures, and feature engineering techniques were applied to derive composite behavioral indicators representing digital activity intensity, sleep regularity, and technology engagement patterns.

2.3. Data analysis

Data analysis was conducted using Python version 3.12 with the Scikit-learn, XGBoost, SHAP, NumPy, Pandas, and Matplotlib libraries. Preliminary descriptive analyses summarized participant characteristics and examined variable distributions. Missing data patterns, outlier detection, feature correlations, and multicollinearity diagnostics were evaluated before predictive modeling. The dataset was randomly divided into training (80%) and independent testing (20%) subsets using stratified sampling to preserve the distribution of participants with and without clinically significant generalized anxiety symptoms. Hyperparameter optimization of the XGBoost classifier was performed using five-fold stratified cross-validation combined with randomized grid search to optimize model complexity while minimizing overfitting. Model performance was evaluated using multiple complementary performance metrics, including accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve (AUC-ROC), area under the precision-recall curve, balanced accuracy, Matthews correlation coefficient, and calibration statistics. Feature importance was initially estimated using the built-in gain-based importance algorithm of XGBoost and subsequently interpreted using SHapley Additive exPlanations (SHAP). Global SHAP summary plots were generated to identify the strongest predictors of generalized anxiety disorder across the entire sample, while local SHAP force plots and waterfall plots were employed to explain individual participant predictions. Partial dependence plots and SHAP dependence plots were additionally produced to investigate nonlinear associations and interaction effects among the most influential predictors. Sensitivity analyses were conducted using repeated stratified cross-validation and bootstrap resampling to examine model robustness and generalizability. Statistical analyses associated with descriptive and preliminary inferential procedures were conducted using a two-sided significance level of $p < .05$, whereas predictive model evaluation emphasized out-of-sample predictive performance and explainability rather than statistical hypothesis testing.

JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518

3. Findings and Results

A total of 2,412 participants were included in the final analyses after quality-control screening. The sample consisted of 1,376 women (57.0%), 1,006 men (41.7%), and 30 participants identifying as non-binary or another gender identity (1.3%). Participants ranged in age from 18 to 69 years (M = 34.82, SD = 11.26). Most participants had completed at least a college or university education (78.9%), while 62.4% were employed either full-time or part-time. Approximately 47.8% were single, 43.5% were married or living with a partner, and the remainder were divorced, separated, or widowed. Based on the recommended GAD-7 cut-off score of 10, 761 participants (31.5%) met the criteria for clinically significant generalized anxiety symptoms, whereas 1,651 participants (68.5%) were classified as having low or minimal anxiety symptoms. Average daily smartphone use across the entire sample was 5.87 hours (SD = 2.34), while participants reported an average sleep duration of 6.71 hours per night (SD = 1.18). The prevalence of previous mental health diagnoses was 28.9%, and approximately 52.6% of participants reported working or studying remotely for at least three days per week. Initial data screening indicated no substantial violations of data quality assumptions following multiple imputation and preprocessing procedures.

Table 1

Descriptive Statistics and Correlations Among Study Variables

Variable	Mean	SD	1	2	3	4	5	6
1. GAD-7 Score	8.94	5.21	—					
2. Psychological Distress (K10)	24.63	8.15	.79**	—				
3. Depression (PHQ-9)	9.81	6.07	.74**	.77**	—			
4. Sleep Quality (PSQI)	8.01	3.54	.61**	.59**	.55**	—		
5. Smartphone Addiction	31.48	10.17	.54**	.50**	.48**	.43**	—	
6. Social Media Addiction	17.92	5.83	.46**	.44**	.42**	.38**	.67**	—

Table 1 presents the descriptive statistics and Pearson correlation coefficients for the principal study variables. Generalized anxiety symptoms demonstrated strong positive associations with psychological distress ($r = .79$, $p < .01$) and depressive symptoms ($r = .74$, $p < .01$), indicating substantial overlap among these indicators of emotional functioning. Sleep quality also showed a moderately strong relationship with anxiety symptoms ($r = .61$, $p < .01$), suggesting that poorer sleep quality was associated with higher levels of generalized anxiety. Measures of problematic smartphone use ($r = .54$, $p < .01$) and problematic social media use ($r = .46$, $p < .01$) exhibited moderate positive correlations with anxiety severity, supporting the hypothesis that maladaptive digital behaviors contribute meaningfully to anxiety symptoms. Correlations among predictor variables ranged from moderate to strong but remained below levels typically associated with severe multicollinearity. These findings indicate that each digital mental health indicator contributed unique information for subsequent machine learning analyses while remaining theoretically related to generalized anxiety disorder.

Table 2

Performance of the Explainable XGBoost Classification Model on the Independent Test Dataset

Performance Metric	Value
Accuracy	91.8%
Precision	89.6%
Recall (Sensitivity)	88.2%
Specificity	93.5%
F1-Score	88.9%
ROC-AUC	0.957
PR-AUC	0.944
Balanced Accuracy	90.9%
Matthews Correlation Coefficient	0.819
Brier Score	0.081

JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518

The predictive performance of the explainable XGBoost classifier is summarized in Table 2. The optimized model demonstrated excellent discrimination between individuals with clinically significant generalized anxiety symptoms and those without generalized anxiety disorder. Overall classification accuracy reached 91.8%, indicating that more than nine out of every ten participants were correctly classified. The ROC-AUC value of .957 reflects outstanding discriminatory ability, while the precision value of 89.6% indicates that the majority of participants predicted to have generalized anxiety disorder were correctly identified. Likewise, the recall value of 88.2% demonstrates that the model successfully detected a very high proportion of true anxiety cases, minimizing false-negative classifications. The specificity of 93.5% further indicates strong performance in correctly identifying participants without generalized anxiety disorder. Additional evaluation indices, including the F1-score (88.9%), balanced accuracy (90.9%), Matthews correlation coefficient (.819), and low Brier score (.081), collectively demonstrate that the XGBoost algorithm achieved highly reliable predictive performance with excellent calibration and minimal classification bias. These findings suggest that explainable gradient boosting techniques provide substantial improvements in prediction accuracy for digital mental health screening applications.

Table 3

Global SHAP Feature Importance Rankings for Predicting Generalized Anxiety Disorder

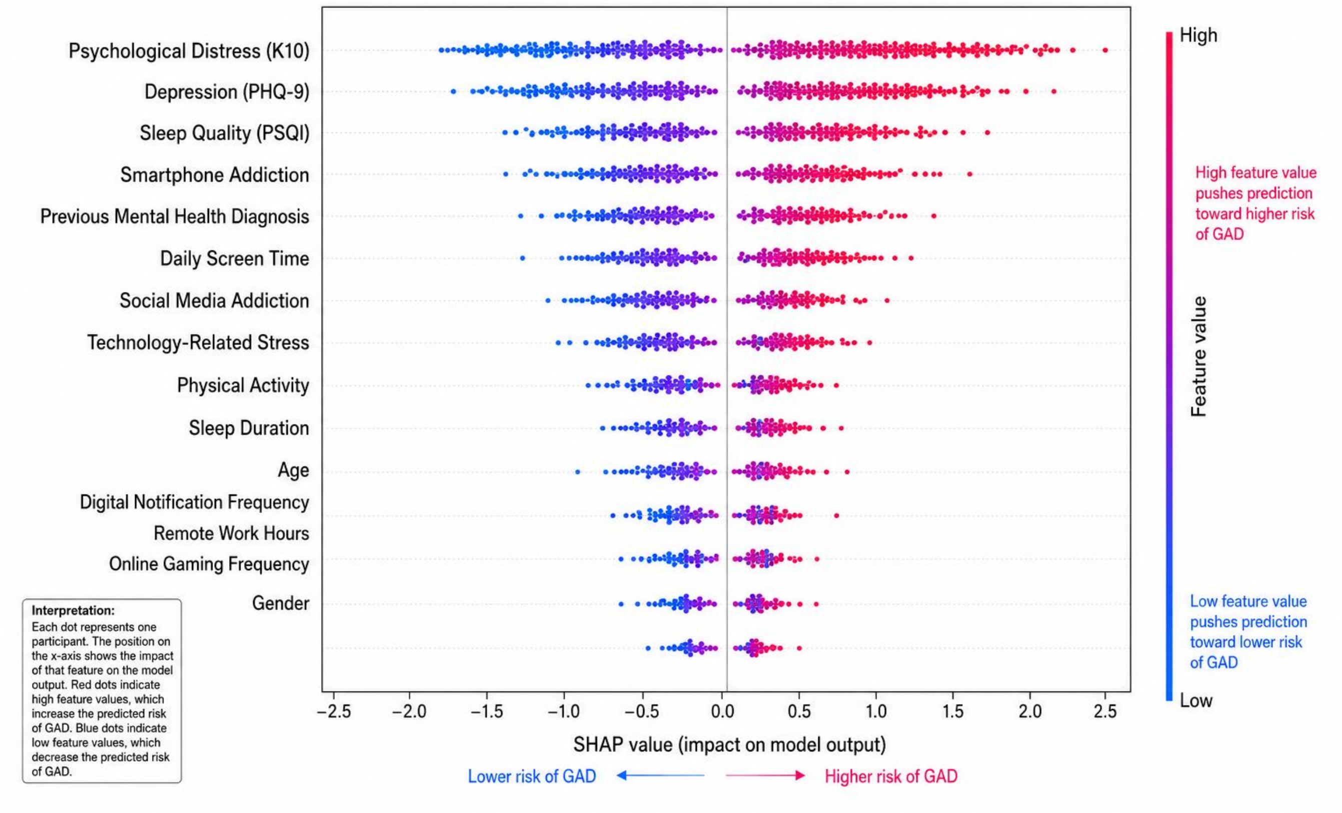
Rank	Predictor	Mean Absolute SHAP Value
1	Psychological Distress (K10)	1.000
2	Depression (PHQ-9)	0.914
3	Sleep Quality (PSQI)	0.723
4	Smartphone Addiction	0.596
5	Previous Mental Health Diagnosis	0.533
6	Daily Screen Time	0.487
7	Social Media Addiction	0.454
8	Technology-Related Stress	0.416
9	Physical Activity	0.382
10	Sleep Duration	0.349
11	Age	0.301
12	Digital Notification Frequency	0.284
13	Remote Work Hours	0.237
14	Online Gaming Frequency	0.198
15	Gender	0.154

Table 3 presents the global feature importance rankings obtained from SHAP analyses, providing interpretable estimates of each predictor's contribution to model decisions. Psychological distress emerged as the single strongest determinant of generalized anxiety disorder prediction, followed closely by depressive symptoms, indicating that emotional distress variables carried the greatest predictive weight. Sleep quality represented the third most influential predictor, demonstrating that disrupted sleep substantially increased the likelihood of generalized anxiety disorder classification. Behavioral indicators of digital technology use, including smartphone addiction, daily screen time, social media addiction, and technology-related stress, also ranked among the most influential predictors, confirming the importance of digital lifestyle characteristics within the predictive model. Previous mental health diagnosis remained a strong contributor, while demographic variables such as age and gender exhibited comparatively smaller contributions. Physical activity demonstrated a protective influence by reducing predicted anxiety risk among participants reporting greater daily movement. Overall, the SHAP rankings indicate that both traditional psychological variables and objectively measurable digital behavior indicators jointly contribute to highly accurate prediction of generalized anxiety disorder.

JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518

Figure 1

SHAP Summary Plot Demonstrating the Global Contribution of Digital Mental Health Indicators to Generalized Anxiety Disorder Prediction



The SHAP summary plot illustrated the direction and magnitude of each predictor's influence on model output across all participants. Higher psychological distress, depressive symptoms, poor sleep quality, excessive smartphone use, greater social media addiction, increased technology-related stress, and prolonged daily screen time consistently shifted predictions toward generalized anxiety disorder. Conversely, higher levels of physical activity, longer sleep duration, fewer digital interruptions, and lower technology dependence shifted predictions toward the non-anxiety classification. The distribution of SHAP values also demonstrated several nonlinear relationships, particularly for screen time and sleep quality, suggesting that anxiety risk increased disproportionately once behavioral thresholds were exceeded. Furthermore, interaction effects were observed between psychological distress and sleep quality, as well as between smartphone addiction and technology-related stress, indicating that combinations of digital behavioral risk factors substantially amplified predicted anxiety probability. The explainability provided by SHAP demonstrated that the XGBoost model produced transparent, clinically interpretable predictions rather than functioning as an opaque "black-box" classifier. Collectively, these findings support the practical applicability of explainable artificial intelligence for individualized digital mental health assessment and early identification of generalized anxiety disorder.

4. Discussion

The present study developed and evaluated an explainable XGBoost model for predicting generalized anxiety disorder from digital mental health indicators in a Canadian adult sample. The findings demonstrated that generalized anxiety symptoms were strongly associated with psychological distress and depressive symptoms, moderately to strongly associated with poor sleep quality, and moderately associated with problematic smartphone use and problematic social media use. At the predictive level, the optimized XGBoost classifier showed excellent performance, with high accuracy, sensitivity, specificity, F1-score, ROC-AUC, PR-AUC, balanced accuracy, and calibration. The SHAP analysis further clarified that psychological distress, depressive symptoms, sleep quality, smartphone addiction, previous mental health diagnosis,

E-ISSN: 3041-8518

daily screen time, social media addiction, technology-related stress, physical activity, and sleep duration were the most influential predictors of generalized anxiety disorder classification. These results support the central assumption of the study: generalized anxiety disorder can be predicted with high accuracy when traditional psychological indicators are integrated with digital behavioral indicators and interpreted through explainable artificial intelligence.

The strong relationship observed between generalized anxiety symptoms, psychological distress, and depression is consistent with the conceptualization of anxiety as part of a broader internalizing spectrum, in which worry, negative affectivity, dysphoria, sleep disturbance, and functional impairment often co-occur. The high predictive importance of psychological distress and depressive symptoms in the SHAP analysis indicates that the XGBoost model relied heavily on clinically plausible emotional indicators rather than arbitrary digital variables. This finding aligns with recent digital mental health studies emphasizing that digital phenotyping should not replace clinical symptom assessment but should strengthen it by adding behavioral and contextual information to conventional measures (Garzón-Partida et al., 2025; Maatoug et al., 2022; Moukaddam et al., 2022). It is also consistent with research protocols and observational models designed to predict depression and anxiety using smartphone and wearable-based indicators, which emphasize that digital features become most meaningful when interpreted alongside validated psychological constructs (Lee & Lee, 2025; Shin et al., 2025). Therefore, the present results suggest that explainable machine learning can preserve clinical coherence while improving predictive precision.

Sleep quality emerged as the third most influential predictor of generalized anxiety disorder, and sleep duration was also among the leading digital lifestyle indicators. This result is theoretically meaningful because generalized anxiety disorder is frequently accompanied by hyperarousal, repetitive worry, difficulty initiating sleep, nighttime rumination, fatigue, and impaired daytime functioning. The current finding supports recent evidence that smartphone-derived rhythms and sleep-related digital signals are associated with anxiety, depression, and sleep disturbance (Winbush et al., 2026). It also corresponds with emerging computational approaches for estimating sleep from smartphone sensors, suggesting that even low-frequency passive sensing may provide useful information about sleep patterns relevant to mental health prediction (Byun et al., 2025). Evidence from wearable device research further supports the clinical relevance of sleep and activity indicators, particularly when consumer-grade sensor information is used cautiously and integrated with psychological data (Hassan et al., 2025). The present model therefore reinforces the importance of sleep as both a symptom domain and a behavioral marker in the prediction of anxiety risk.

The predictive role of smartphone addiction, daily screen time, social media addiction, and technology-related stress indicates that digital behavior is meaningfully associated with generalized anxiety disorder classification. These findings support the view that anxiety-related risk may be reflected in patterns of excessive device engagement, compulsive checking, notification sensitivity, online reassurance seeking, social comparison, and difficulty disengaging from digital environments. App-based ecological momentary assessment research on problematic smartphone use has shown that smartphone behavior can be monitored in real time and may fluctuate during high-stress periods, such as examination weeks among university students (Ahn et al., 2025). Similarly, research on digital media use in young adults has indicated that the process of monitoring digital behavior may itself increase awareness and produce behavioral changes, suggesting that digital indicators are not merely passive markers but may become targets for self-regulation (Jo et al., 2025). The observed role of social media addiction is also consistent with research on social media detox and youth mental health, which highlights the potential mental health relevance of reducing or restructuring digital social exposure (Calvert et al., 2025). Together, these findings suggest that problematic digital engagement may represent both a correlate and a potential maintenance factor of generalized anxiety symptoms.

The present findings also contribute to the broader literature on digital phenotyping by showing that digital mental health indicators can be useful for anxiety-specific prediction, not only for depression, bipolar disorder, schizophrenia, or severe mental illness. Previous reviews and feasibility studies have shown that digital phenotyping can capture behavioral patterns relevant to mood disorders, functional impairment, and symptom fluctuation (Breitinger et al., 2023; Bufano et al., 2023; Fulford & Jacobson, 2025). Research on active and passive ambulatory assessment in bipolar disorder has similarly demonstrated that digital and mobile monitoring can contribute to understanding symptom patterns, although methodological standardization remains necessary (Wright et al., 2026). Studies integrating cognitive, functional, and digital phenotyping assessments

JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518

in schizophrenia further illustrate that digital features can help identify clinically meaningful profiles beyond traditional diagnostic categories (Byun et al., 2024). Although generalized anxiety disorder differs from these conditions in symptom structure and clinical expression, the present findings suggest that digital phenotyping principles can be extended to anxiety prediction when variables are selected based on psychological plausibility and interpreted through transparent analytic methods.

The high performance of the XGBoost model supports the growing use of machine learning in digital mental health research. The model achieved strong discrimination and calibration, indicating that it was able to identify individuals with clinically significant generalized anxiety symptoms while also maintaining a low rate of false-positive and false-negative classifications. This result is consistent with machine learning literature emphasizing the value of binary classification models for mental health prediction, particularly when the aim is to distinguish high-risk from low-risk individuals (Choudhary & Srinivasan, 2022). It also supports the argument that small-data and personalized machine learning approaches can contribute to precision psychiatry when models are carefully validated and grounded in meaningful behavioral indicators (Wang et al., 2025). The findings are also compatible with recent proposals for integrating artificial intelligence and smartphone technology to support personalized mental health assessment and intervention, where computational models are expected to inform individualized decision-making rather than produce generic screening outcomes (Linardon & Torous, 2025). In this regard, the present study demonstrates that explainable XGBoost can serve as a powerful analytic framework for combining clinical, behavioral, and digital variables into a single anxiety prediction model.

A central strength of the present study is the use of explainable artificial intelligence, particularly SHAP analysis, to interpret model behavior. The SHAP rankings showed that the model assigned greatest importance to psychological distress, depression, sleep quality, smartphone addiction, prior mental health diagnosis, screen time, social media addiction, technology-related stress, physical activity, and sleep duration. This hierarchy of predictors is clinically interpretable and consistent with current work on passive sensing, ecological momentary assessment, and digital biomarkers. Studies of digital phenotyping in cancer, long COVID, obsessive-compulsive disorder, and mood disorders have demonstrated that digital measures are most useful when they can be connected to meaningful symptom trajectories, daily functioning, and treatment-relevant outcomes (Frank et al., 2023; Garzón-Partida et al., 2025; Jenciūtė et al., 2023; Mansoubi et al., 2023). The present study extends this logic to generalized anxiety disorder by showing not only that prediction is possible, but also that the model's predictions can be explained in terms of psychologically coherent risk factors. This is important because clinical implementation of artificial intelligence requires transparency, interpretability, and confidence that model decisions are not driven by irrelevant or biased features.

The inverse contribution of physical activity to anxiety prediction also deserves attention. In the SHAP interpretation, greater physical activity shifted predictions toward lower generalized anxiety risk, whereas reduced activity contributed to higher predicted risk. This finding is consistent with digital phenotyping frameworks that treat mobility and activity as behavioral markers of emotional functioning and psychopathology (Fulford & Jacobson, 2025; Mendes et al., 2022). It also aligns with the broader premise of passive sensing research: changes in daily routines, movement patterns, sleep, and engagement may serve as early indicators of mental health deterioration. Although the present study did not test physical activity as an intervention mechanism, the result suggests that activity-related indicators may contribute useful protective information in anxiety prediction models. This also reinforces the need to interpret digital mental health indicators multidimensionally. Not all digital variables represent risk; some, such as regular physical activity, sufficient sleep, and stable routines, may function as protective signals that improve model discrimination and support more nuanced clinical interpretation.

The results also have implications for intervention development. The fact that technology-related stress, smartphone addiction, screen time, and social media addiction contributed to generalized anxiety disorder prediction suggests that digital behavior may be a relevant intervention target. Recent digital interventions for anxiety and depression, including digital positive affect interventions and AI-driven just-in-time adaptive intervention mechanisms, illustrate how mobile systems may be used not only to assess risk but also to deliver timely support (Zainal et al., 2025; Zarski et al., 2025). Longitudinal protocols examining wearable- and ecological momentary assessment-based predictors of non-response to cognitive behavioral therapy for internalizing disorders

JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518

further show that digital phenotypes may help identify who is less likely to respond to standard treatment and who may need adaptive or intensified care (Hammelrath et al., 2025a, 2025b). The present findings therefore suggest that explainable prediction models could eventually be embedded into stepped-care systems, digital screening platforms, or personalized intervention tools, provided that ethical safeguards, privacy protections, and clinical validation are ensured.

The study's findings also correspond with the broader literature on mobile assessment and digital monitoring in youth and adult populations. Umbrella reviews of mobile mental health assessments have emphasized that smartphones can support high-frequency, ecologically valid monitoring of psychological states, although questions remain regarding adherence, engagement, measurement burden, and data validity (Marciano et al., 2023a, 2023b). Studies of ecological momentary assessment among adults with suicide risk have similarly demonstrated the feasibility of repeated digital assessment in clinically vulnerable groups, while also highlighting the importance of adherence and participant acceptability (Kim et al., 2025). The present study used digital mental health indicators within a predictive modeling framework, but its findings also point to the need for careful implementation. Predictive accuracy alone is insufficient if users do not trust the system, if digital measures are burdensome, or if the results are not actionable for clinicians. Therefore, the value of explainable XGBoost lies not only in statistical performance but also in its ability to support understandable, individualized, and potentially actionable risk profiles.

5. Conclusion

Overall, the present study advances the field by demonstrating that generalized anxiety disorder can be predicted with high accuracy using a combination of psychological symptoms, sleep-related indicators, digital behavior variables, and demographic information. The results are consistent with the growing movement toward precision psychiatry, in which digital phenotyping, passive sensing, ecological momentary assessment, and machine learning are combined to produce individualized mental health insights (Fulford & Jacobson, 2025; Moukaddam et al., 2022; Wang et al., 2025). The findings particularly emphasize that anxiety prediction benefits from integrating both conventional clinical indicators and everyday digital behavior markers. The model's explainability further strengthens its scientific and potential clinical value by showing that predictions were primarily shaped by meaningful psychological and behavioral variables rather than opaque algorithmic patterns. In this sense, the study contributes to the development of transparent digital mental health screening methods that may improve early identification, risk stratification, and personalized prevention of generalized anxiety disorder.

6. Limitations & Suggestions

Limitations should be acknowledged when interpreting the findings. First, the cross-sectional design prevents conclusions about causal direction among psychological distress, digital behavior, sleep quality, and generalized anxiety disorder. Although the XGBoost model demonstrated strong predictive performance, prediction does not establish whether digital behaviors caused anxiety symptoms or whether anxious individuals were more likely to engage in maladaptive digital behaviors. Second, several indicators were based on self-report, which may introduce recall bias, social desirability bias, and measurement error. Third, although the sample was large and drawn from Canada, it may not fully represent all demographic, cultural, socioeconomic, linguistic, and clinical subgroups. Fourth, the classification outcome was based on symptom severity rather than structured clinical diagnosis. Fifth, although SHAP improved model interpretability, explainability methods provide estimates of feature contribution rather than definitive causal mechanisms.

Future research should use longitudinal, multi-wave, and real-time data collection designs to clarify temporal relationships between digital behavior and generalized anxiety symptoms. Studies should integrate passive smartphone sensing, wearable device data, ecological momentary assessment, clinical interviews, and objective sleep and activity metrics to strengthen measurement validity. Future investigations should also test whether explainable XGBoost models maintain accuracy across age groups, genders, socioeconomic groups, provinces, clinical populations, and culturally diverse communities. External validation in independent Canadian and international samples is essential before clinical implementation. Additional research should compare XGBoost with other machine learning and deep learning approaches, examine fairness and bias across demographic subgroups, and determine whether digital prediction models can identify anxiety risk before symptom escalation occurs. Intervention

JARAC Assessment and Research in Applied Counseling E-ISSN: 3041-8518

studies are also needed to examine whether model-informed feedback can improve early detection, treatment matching, and personalized prevention.

Suggestions for practice include cautious integration of explainable digital prediction tools into mental health screening and preventive care systems. Clinicians, counselors, digital health developers, and public health organizations may use models of this type to identify individuals who may benefit from further assessment, psychoeducation, sleep-focused support, digital behavior regulation, stress management, or referral to professional care. However, such models should be used as decision-support tools rather than replacements for clinical judgment. Screening outputs should be communicated in accessible language, and users should understand which factors contributed to their risk estimate. Privacy, informed consent, transparency, data security, and non-stigmatizing feedback are essential for ethical implementation. In practice, the most useful application of explainable XGBoost models may be to support early recognition of anxiety risk and guide personalized, low-burden interventions before symptoms become chronic or functionally disabling.

Acknowledgments

We would like to express our appreciation and gratitude to all those who cooperated in carrying out this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

Authors' Contributions

All authors equally contributed in this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

References

Ahn, J. S., Jeong, I., Park, S., Lee, J., Jeon, M.-J., Lee, S., Do, G., Jung, D., & Park, J. Y. (2025). App-Based Ecological Momentary Assessment of Problematic Smartphone Use During Examination Weeks in University Students: 6-Week Observational Study. *Journal of medical Internet research*, *27*, e69320. https://doi.org/10.2196/69320

Breitinger, S., Gardea-Resendez, M., Langholm, C., Xiong, A., Laivell, J., Stoppel, C., Harper, L., Volety, R., Walker, A. J., D'Mello, R., Byun, A. J. S., Zandi, P. P., Goes, F. S., Frye, M. A., & Torous, J. (2023). Digital Phenotyping for Mood Disorders: Methodology-Oriented Pilot Feasibility Study. *Journal of medical Internet research*, *25*, e47006. https://doi.org/10.2196/47006

Bufano, P., Laurino, M., Said, S., Tognetti, A., & Menicucci, D. (2023). Digital Phenotyping for Monitoring Mental Disorders: Systematic Review (Preprint). https://doi.org/10.2196/preprints.46778

Byun, A., Lane, E., Langholm, C., Flathers, M., Hall, M. H., & Torous, J. (2024). Towards Clinical Subtypes in Schizophrenia: Integrating Cognitive, Functional, and Digital Phenotyping Assessments. https://doi.org/10.21203/rs.3.rs-4258332/v1

Byun, A. J. S., Li, Y., Cong, S., Dhima, A., Wang, S., Flathers, M., & Torous, J. (2025). Sleep Estimation From Low Frequency Smartphone Sensors via Bayesian Hidden Markov Model. https://doi.org/10.21203/rs.3.rs-7217304/v1

Calvert, E., Dwyer, B., Lisowski, V., Mikkelson, J., Chen, K., Flathers, M., Hau, C., Xia, W., Martínez, J. A. C., Dhima, A., Ryan, S., & Torous, J. (2025). Social Media Detox and Youth Mental Health. *JAMA Network Open*, *8*(11), e2545245. https://doi.org/10.1001/jamanetworkopen.2025.45245

Choudhary, S., & Srinivasan, G. (2022). The Importance of Using Binary Classification Models in Predicting Depression From a Machine Learning Perspective. *Digital Medicine and Healthcare Technology*, *2022*, 1-4. https://doi.org/10.5772/dmht.12

Frank, A. C., Li, R., Peterson, B. S., & Narayanan, S. (2023). Wearable and Mobile Technologies for the Evaluation and Treatment of Obsessive-Compulsive Disorder: Scoping Review (Preprint). https://doi.org/10.2196/preprints.45572

Fulford, D., & Jacobson, N. C. (2025). Passive Sensing of Behavioral Markers of Psychopathology: Introduction to the Special Issue. *Journal of Psychopathology and Clinical Science*, *134*(8), 855-859. https://doi.org/10.1037/abn0001035

Garzón-Partida, A. P., Padilla-Gómez, C. B., Fernández, D., García-Estrada, J. n., Luquín, S., & Fernández-Quezada, D. (2025). The Implementation of Digital Biomarkers in the Diagnosis, Treatment and Monitoring of Mood Disorders: A Narrative Review. *Frontiers in Digital Health*, *7*. https://doi.org/10.3389/fdgth.2025.1595243

JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518

Hammelrath, L., Brose, A., Heinrich, M., Zagorscak, P., Burchert, S., Langhammer, T., & Knaevelsrud, C. (2025a). PREACT-digital: Study Protocol for a Longitudinal, Observational Multi-Center Study on Wearable- And EMA- Based Predictors of Non-Response to CBT for Internalizing Disorders. https://doi.org/10.1101/2025.03.14.25323957

Hammelrath, L., Brose, A., Heinrich, M., Zagorscak, P., Burchert, S., Langhammer, T., & Knaevelsrud, C. (2025b). PREACT-digital: Study Protocol for a Longitudinal, Observational Multicentre Study on Digital Phenotypes of Non-Response to Cognitive Behavioural Therapy for Internalising Disorders. *BMJ open*, *15*(7), e102392. https://doi.org/10.1136/bmjopen-2025-102392

Hassan, L., Milton, A., Sawyer, C., Casson, A. J., Torous, J., Davies, A., Ruiz-Yu, B., & Firth, J. (2025). Utility of Consumer-Grade Wearable Devices for Inferring Physical and Mental Health Outcomes in Severe Mental Illness: Systematic Review. *Jmir Mental Health*, *12*, e65143. https://doi.org/10.2196/65143

Jenciūtė, G., Kasputytė, G., Bunevičienė, I., Korobeinikova, E., Vaitiekus, D., Inčiūra, A., Jaruševičius, L., Bunevičius, R., Krikštolaitis, R., Krilavičius, T., Juozaitytė, E., & Bunevičius, A. (2023). Digital Phenotyping for Monitoring and Disease Trajectory Prediction of Patients With Cancer: Protocol for a Prospective Observational Cohort Study. *Jmir Research Protocols*, *12*, e49096. https://doi.org/10.2196/49096

Jo, S. J., Lee, H. K., Kwon, S. J., Kim, Y., Kwak, J. S., & Lee, h. (2025). Unintended Positive Behavioral Changes During Self-Report and Wearable Data Collection On digital Media Use in Young Adults. *Journal of Behavioral Addictions*, *14*(4), 1619-1624. https://doi.org/10.1556/2006.2025.00082

Kim, H., Kwon, S., Park, S., Kang, C., & Kim, H. (2025). Feasibility and Adherence to Ecological Momentary Assessment Among Community-Dwelling Adults With Suicide Risk. *BMC Nursing*, *24*(1). https://doi.org/10.1186/s12912-025-03432-y

Lee, Y.-R., & Lee, J.-S. (2025). Real-Time Monitoring to Predict Depressive Symptoms: Study Protocol. *Frontiers in Psychiatry*, *15*. https://doi.org/10.3389/fpsyt.2024.1465933

Linardon, J., & Torous, J. (2025). Integrating Artificial Intelligence and Smartphone Technology to Enhance Personalized Assessment and Treatment for Eating Disorders. *International Journal of Eating Disorders*, *58*(8), 1415-1424. https://doi.org/10.1002/eat.24468

Maatoug, R., Oudin, A., Adrien, V., Saudreau, B., Bonnot, O., Millet, B., Ferreri, F., Mouchabac, S., & Bourla, A. (2022). Digital Phenotype of Mood Disorders: A Conceptual and Critical Review. *Frontiers in Psychiatry*, *13*. https://doi.org/10.3389/fpsyt.2022.895860

Mansoubi, M., Dawes, J., Bhatia, A., Vashisht, H., Collett, J., Greenwood, D. C., Ezekiel, L., O'Connor, D. B., Leveridge, P., Rayner, C., Read, F., Sivan, M., Tucker-Bell, I., Ward, T., Delaney, B., Muhlhausen, W., & Dawes, H. (2023). Digital Home Monitoring for Capturing Daily Fluctuation of Symptoms; A Longitudinal Repeated Measures Study: Long Covid Multi-Disciplinary Consortium to Optimise Treatments and Services Across the NHS (A LOCOMOTION Study). *BMJ open*, *13*(8), e071428. https://doi.org/10.1136/bmjopen-2022-071428

Marciano, L., Vocaj, E., Bekalu, M. A., Tona, A. L., Rocchi, G., & Viswanath, K. (2023a). The Use of Mobile Assessments for Monitoring Mental Health in Youth: Umbrella Review. *Journal of medical Internet research*, *25*, e45540. https://doi.org/10.2196/45540

Marciano, L., Vocaj, E., Bekalu, M. A., Tona, A. L., Rocchi, G., & Viswanath, K. (2023b). The Use of Mobile Assessments for Monitoring Mental Health in Youth: Umbrella Review (Preprint). https://doi.org/10.2196/preprints.45540

Mendes, J. P. M., Moura, I. R. d., Ven, P. V. d., Viana, D., Silva, F., Coutinho, L., Teixeira, S., Joel, J. P. C. R., & Teles, A. S. (2022). Sensing Apps and Public Data Sets for Digital Phenotyping of Mental Health: Systematic Review. *Journal of medical Internet research*, *24*(2), e28735. https://doi.org/10.2196/28735

Moukaddam, N., Sano, A., Salas, R., Hammal, Z., & Sabharwal, A. (2022). Turning Data Into Better Mental Health: Past, Present, and Future. *Frontiers in Digital Health*, *4*. https://doi.org/10.3389/fdgth.2022.916810

Shin, Y., Kim, A. Y., Kim, S., Shin, M. S., Lee, K. L., Lee, J. S., Byun, S., Kim, S., & Cho, C. H. (2025). Development of Prediction Models for Screening Depression and Anxiety Using Smartphone and Wearable-Based Digital Phenotyping: Protocol for the Smartphone and Wearable Assessment for Real-Time Screening of Depression and Anxiety (SWARTS-DA) Observational Study in Korea. *BMJ open*, *15*(6), e096773. https://doi.org/10.1136/bmjopen-2024-096773

Wang, P., Liu, H., Shi, Y., Liu, A., Zhu, Q., Albu, I., Pacholec, M., Cheng, L., Sun, X., & Chi, X. (2025). Harnessing Small-Data Machine Learning for Transformative Mental Health Forecasting: Towards Precision Psychiatry With Personalised Digital Phenotyping. *Med Research*, *1*(2), 226-238. https://doi.org/10.1002/mdr2.70017

Winbush, A., McDuff, D., Nelson, B., Heneghan, C., Hernandez, J., & Allen, N. B. (2026). Smartphone-Derived Biobehavioral Rhythms and Their Associations With Depression, Anxiety, and Sleep Disturbance. https://doi.org/10.21203/rs.3.rs-9633601/v1

Wright, L. A., Bakštein, E., Saunders, K., Guo, B., & Morriss, R. (2026). Performance of Active and Passive Ambulatory Assessment Measures and Mood Monitoring in Bipolar Disorder: A Systematic Review. *International Journal of Bipolar Disorders*, *14*(1). https://doi.org/10.1186/s40345-025-00407-5

Zainal, N. H., Rajendra, S. J., Doren, N. V., Salamanca-Sanabria, A., Curtiss, J., & Keng, S. L. (2025). Digital Positive Affect Intervention (PAI) Versus Self-Monitoring Placebo in the Treatment of Anxiety and Depression: A Two-Arm Randomized Controlled Trial (RCT). *BMC psychiatry*, *25*(1). https://doi.org/10.1186/s12888-025-07372-4

Zarate, D., Stavropoulos, V., Ball, M. B., Collier, G. d. S., & Jacobson, N. C. (2022). Exploring the Digital Footprint of Depression: A PRISMA Systematic Literature Review of the Empirical Evidence. https://doi.org/10.31234/osf.io/tqvfk

Zarski, A. C., Sextl-Plötz, T., Schmidt-Hantke, J., Hess, N. S., & Buntrock, C. (2025). Participatory Development and Proof-of-Concept of a Dyadic-Based, AI-driven, Just-in-Time Adaptive Intervention Mechanism for Preventing Anxiety and Depressive Disorders via App: Study Protocol for a Feasibility Study. *Frontiers in Public Health*, *13*. https://doi.org/10.3389/fpubh.2025.1626428

JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518