Anxiety Prediction Model Based on Smartwatch Activity Data and Self-Reported Affect Scale in Adolescents

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ABSTRACT

Anxiety among adolescents is a growing public health concern and is frequently underdetected due to reliance on subjective assessments and limited continuous monitoring. Wearable technologies offer new opportunities to capture real-time physiological and behavioral indicators that may enhance early detection. **This study aims** to develop and evaluate an anxiety prediction model that integrates smartwatch-derived activity data with a validated self-reported affect scale to improve detection accuracy in adolescents. **A longitudinal** study was conducted involving adolescent participants monitored over several weeks. Objective data collected from smartwatches included heart rate variability, sleep duration, physical activity intensity, and daily movement patterns. These indicators were combined with subjective emotional states measured using a validated affect scale. Machine learning algorithms were employed to build predictive models, and performance was evaluated using accuracy, precision, recall, and F1-score metrics. **The integrated model** demonstrated superior predictive performance compared to single-source models based solely on wearable or self-reported data. The findings indicate that combining physiological, behavioral, and affective measures significantly improves anxiety classification accuracy. **The proposed** approach provides a scalable, non-invasive, and real-time framework for early anxiety detection among adolescents. This study contributes to the advancement of human-centered digital mental health systems and highlights the potential of wearable-based analytics for preventive and personalized mental healthcare interventions.

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1. INTRODUCTION

Adolescent anxiety has emerged as a critical global public health issue, affecting emotional stability, academic engagement, and long-term psychological development. According to international health reports, anxiety disorders constitute one of the leading contributors to mental health burdens among adolescents worldwide. Despite increasing awareness, anxiety in this population often remains underrecognized due to limited access to mental health services, reliance on episodic self-report assessments, and social stigma surrounding psychological distress [1]. These challenges directly hinder the achievement of Sustainable Development Goal (SDG) 3, which emphasizes ensuring healthy lives and promoting well-being for all at all ages. Early and continuous detection of anxiety is essential to mitigate its adverse consequences on adolescents' well-being and educational outcomes. Untreated anxiety can negatively influence concentration, school attendance, and academic performance, thereby intersecting with SDGs 4 (Quality Education), which aims to ensure inclusive and equitable education and promote lifelong learning opportunities [2]. However, conventional mental health assessment approaches are typically reactive, subjective, and dependent on clinical settings, limiting their effectiveness in large-scale preventive monitoring, especially in school-aged populations.

The rapid advancement of wearable technologies, particularly smartwatches, offers a promising avenue for addressing these limitations. Smartwatches enable continuous and non-invasive monitoring of physiological and behavioral indicators such as heart rate variability, sleep duration, physical activity levels, and daily movement patterns. Prior studies have demonstrated associations between these indicators and psychological states related to stress and anxiety [3, 4]. By capturing real-world, longitudinal data, wearable devices support proactive mental health surveillance aligned with the preventive focus advocated by SDGs 3. Nevertheless, physiological and activity-based data alone may not fully capture the subjective nature of anxiety, which is inherently linked to personal emotional experiences [5]. Self-reported affect scales remain a crucial component in mental health research, as they provide insight into adolescents' perceived emotional states and daily mood fluctuations. Integrating subjective affective measures with objective smartwatch data allows for a more comprehensive and human-centered understanding of anxiety, ensuring that technological solutions remain sensitive to individual experiences rather than relying solely on biometric signals [6].

Machine learning techniques play a pivotal role in transforming multimodal data into meaningful predictive insights. By analyzing complex, high-dimensional datasets, machine learning models can uncover temporal and nonlinear relationships between smartwatch activity patterns and self-reported affect that are difficult to detect using traditional analytical methods. The application of machine learning in adolescent mental health monitoring supports scalable, data-driven decision-making and facilitates early identification of anxiety risk, contributing to equitable access to mental health support as envisioned by the SDGs [7]. Despite growing interest in digital mental health solutions, empirical studies that focus on adolescents and integrate smartwatch activity data with validated affect scales within an SDG-oriented framework remain limited. Many existing studies concentrate on adult populations or rely on single-source data, reducing predictive accuracy and practical applicability [8, 9]. Addressing this gap, the present study proposes an anxiety prediction model that combines smartwatch-derived activity data and self-reported affect scales using machine learning approaches. The objective is to enhance prediction accuracy, support early intervention, and promote adolescent well-being in both healthcare and educational contexts [10].

By aligning wearable-based anxiety prediction with SDGs 3 and SDGs 4, this research contributes to the development of sustainable, inclusive, and preventive digital health technologies. The proposed model offers a scalable solution for real-time anxiety monitoring, supporting schools, families, and healthcare providers in fostering healthier learning environments and improving mental health outcomes for adolescents [11]. Ultimately, this study underscores the potential of integrating human-centered wearable analytics into broader sustainable development agendas for future mental healthcare systems.

2. RESEARCH METHOD

This section describes the methodological procedures employed to develop and evaluate the adolescent anxiety prediction model proposed in this study. It outlines the research design, theoretical foundation, sampling strategy, data collection instruments, preprocessing techniques, model development process, and evaluation metrics used to ensure methodological rigor and analytical validity. Given the objective of integrating physiological, behavioral, and affective data within a machine learning framework, a structured and systematic approach was adopted to ensure reliability, reproducibility, and empirical robustness [12]. The methodological framework was designed to capture longitudinal variations in adolescent activity patterns and emotional states, thereby enabling accurate and scalable anxiety prediction. The following subsections present the research paradigm, conceptual framework, data collection procedures, and analytical techniques in detail [13].

2.1. Research Paradigm and Methodological Approach

This study is grounded in a positivist research paradigm, which assumes that adolescent anxiety can be objectively measured and predicted using observable physiological, behavioral, and affective indicators. A quantitative research approach is employed to analyze numerical data derived from smartwatch activity records and self-reported affect scales [14]. This approach is appropriate for predictive modeling and supports evidence-based decision-making in digital mental health research. A longitudinal observational design is adopted to enable continuous monitoring of adolescents over an extended period. Longitudinal data collection is essential for capturing day to day fluctuations in physical activity, sleep behavior, emotional states, and anxiety levels [15, 16]. This design reflects current best practices in wearable-based mental health research and supports early detection of anxiety in adolescent populations.

2.2. Theoretical Basis and Literature-Informed Methodological Foundation

The methodological framework of this study is informed by contemporary literature in four interrelated domains: adolescent anxiety, wearable-based mental health monitoring, affective measurement, and machine learning applications in healthcare [17, 18]. Previous studies consistently report that anxiety is one of the most prevalent yet underdetected mental health conditions among adolescents, with substantial implications for academic performance and psychosocial development. Research on wearable technologies demonstrates that physiological indicators such as heart rate variability and sleep duration, as well as behavioral indicators such as physical activity intensity and movement patterns, are significantly associated with stress and anxiety-related states [19]. However, anxiety is inherently subjective and cannot be fully inferred from physiological data alone. Affective science literature emphasizes that self-reported affect scales are critical for capturing internal emotional experiences that complement objective sensor-based measurements. Recent advances in machine learning highlight the effectiveness of multimodal data integration in improving prediction accuracy for mental health outcomes. Despite these advances, existing studies frequently focus on adult populations or rely on single-source data. This study addresses this gap by integrating smartwatch-derived activity data with self-reported affect to develop an anxiety prediction model specifically for adolescents [20, 21].

2.3. Research Framework and Hypothesis Development

Based on the literature synthesis, a conceptual research framework is developed to explain how objective smartwatch-derived indicators and subjective affective states jointly contribute to anxiety prediction in adolescents [22]. The framework positions self-reported affect as a mediating construct, reflecting the psychological mechanism through which physiological and behavioral changes influence anxiety.

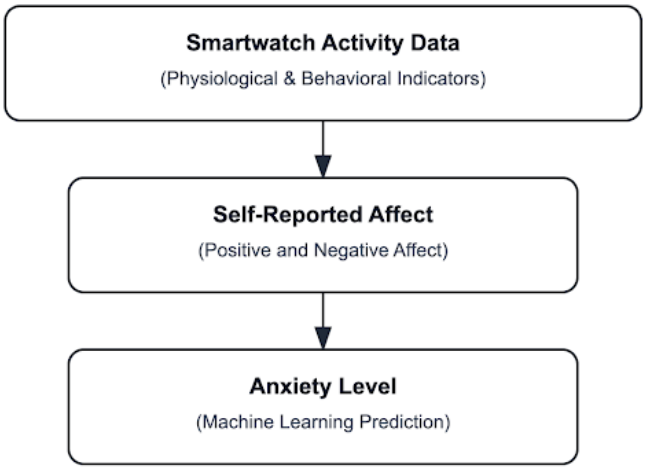

Figure 1. Research Framework for Adolescent Anxiety Prediction

Figure 1 presents the research framework for adolescent anxiety prediction, illustrating the sequential relationship between objective smartwatch-derived data, subjective emotional assessment, and mental health outcomes [23]. In this framework, smartwatch activity data consisting of physiological indicators (such as heart rate variability and sleep duration) and behavioral indicators (including physical activity intensity, step count, and movement patterns) function as the primary independent variables collected continuously and non-invasively [24]. These indicators influence adolescents' emotional conditions, which are represented by self-reported affect encompassing both positive and negative affect and positioned as a mediating variable that captures subjective emotional experiences not fully observable through biometric signals. The final outcome of the framework is the anxiety level of adolescents, which is predicted using machine learning models that integrate both smartwatch activity data and self-reported affect to identify complex and nonlinear patterns [25]. This integrated framework supports early and continuous anxiety detection, emphasizes a human-centered digital health approach, and aligns with the preventive mental health objectives of SDGs 3 (Good Health and Well-Being) as well as the educational sustainability focus of SGDs 4 (Quality Education) [26].

Hypotheses

- H1: Physiological indicators derived from smartwatch activity data significantly predict adolescent anxiety levels.
- H2: Behavioral activity indicators derived from smartwatch data significantly predict adolescent anxiety levels.
- H3: Self-reported affect mediates the relationship between smartwatch activity data and adolescent anxiety.
- H4: Integrated multimodal data provide higher anxiety prediction accuracy than single-source data models.

2.4. Population and Sampling

The study population consists of adolescents aged 13–18 years. A purposive sampling technique is applied to recruit participants who regularly use smartwatches, are willing to complete daily affect assessments, and have obtained parental or guardian consent. This sampling strategy ensures the relevance and reliability of data used for predictive modeling [27]. Rather than relying solely on traditional inferential sample size calculations, this study emphasizes data sufficiency for machine learning, ensuring an adequate number of observations for model training, validation, and testing.

2.5. Data Collection Instruments and Procedures

Data collection is conducted over multiple consecutive weeks to capture both short-term and longer-term behavioral patterns. Smartwatches automatically record physiological and behavioral indicators at regular intervals, while affective data are collected once daily through a mobile-based self-report questionnaire [28]. Anxiety levels are measured using a standardized and validated adolescent anxiety scale administered at baseline and follow-up stages.

Table 1. Variables and Measurement Instruments

Variable Category	Indicators	Measurement Tool
Physiological	Heart rate variability, sleep duration	Smartwatch sensors
Behavioral	Physical activity intensity, step count	Smartwatch activity logs
Affective	Positive affect, negative affect	Validated affect scale
Anxiety	Anxiety severity score	Standardized anxiety questionnaire

Table 1 summarizes the key variables used in this study along with their respective indicators and measurement instruments. Physiological variables are represented by heart rate variability and sleep duration, which are objectively captured through smartwatch sensors to reflect adolescents' autonomic responses and recovery patterns associated with anxiety [29, 30]. Behavioral variables include physical activity intensity and step count, obtained from smartwatch activity logs, providing insight into daily movement patterns and lifestyle behaviors that are often linked to psychological well-being. Affective variables are measured using a validated affect scale that assesses positive and negative affect, allowing the study to capture adolescents' subjective emotional states that may mediate the relationship between activity patterns and anxiety. Finally, anxiety is operationalized through an anxiety severity score derived from a standardized anxiety questionnaire, ensuring reliable and valid assessment of the dependent variable for model training and evaluation [31].

2.6. Data Preprocessing and Feature Engineering

Raw data obtained from smartwatches and self-reported questionnaires undergo systematic preprocessing. This includes noise reduction, handling missing values through statistical imputation, and normalization to ensure consistency across features [32]. Feature engineering techniques are applied to extract meaningful temporal features, such as daily averages, variability, and trend-based indicators, which enhance model interpretability and predictive performance.

2.7. Anxiety Prediction Model Development

Supervised machine learning algorithms are employed to develop anxiety prediction models. Algorithms commonly used in current digital mental health research such as logistic regression, random forest, support vector machines, and gradient boosting are evaluated and compared. The dataset is partitioned into training, validation, and testing subsets using k-fold cross-validation to ensure model robustness and generalizability [33].

$$\hat{A} = f(P, B, F) \tag{1}$$

Where:

$$\begin{aligned} \hat{A} &= \text{predicted anxiety level} \\ P &= \text{physiological features} \\ B &= \text{behavioral features} \\ F &= \text{affective features} \end{aligned}$$

2.8. Model Evaluation

Model performance is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score [34]. These metrics provide a comprehensive assessment of the model's ability to correctly identify adolescents at different anxiety levels.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

Comparative evaluation is conducted between smartwatch-only models, affect-only models, and integrated multimodal models to assess the contribution of data integration [35].

3. RESULTS AND DISCUSSION

3.1. Results

This section presents the empirical findings derived from the longitudinal data collected through smartwatch monitoring and self-reported affect assessments. The analysis is structured in accordance with the proposed research framework and hypotheses, beginning with descriptive statistics to provide an overview of the sample characteristics and variable distributions. Subsequent subsections report the predictive model performance and mediation analysis results to evaluate the relationships among physiological, behavioral, affective, and anxiety variables [36]. The findings are presented systematically to demonstrate the robustness of the integrated multimodal anxiety prediction model.

Table 2. Descriptive Statistics of Study Variables

Variable	Mean	SD	Min	Max
Heart Rate Variability (ms)	45.62	11.38	21.40	79.85
Sleep Duration (hours)	6.57	1.14	4.02	9.21
Daily Step Count	6.384	1.987	1.520	13.476
Physical Activity Intensity	0.61	0.17	0.25	0.94
Positive Affect	3.18	0.74	1.40	4.80
Negative Affect	2.96	0.88	1.10	4.90
Anxiety Severity Score	15.24	5.12	5.00	29.00

3.1.1. Descriptive Statistics

The longitudinal data collection generated 1,248 daily observations from 78 adolescent participants. After preprocessing and feature engineering, the key statistical characteristics of the study variables are presented in Table 2 [37].

As presented in Table 2, the descriptive statistics provide an overview of the physiological, behavioral, affective, and anxiety-related variables collected from adolescent participants during the longitudinal monitoring period. The mean heart rate variability (M = 45.62, SD = 11.38) indicates moderate autonomic regulation across participants, while the average sleep duration (M = 6.57 hours, SD = 1.14) suggests that a substantial proportion of adolescents may be experiencing suboptimal sleep relative to recommended guidelines [38]. Behavioral indicators show an average daily step count of 6,384 steps (SD = 1,987), reflecting moderate physical activity levels with considerable variability among participants [39]. In terms of affective measures, the mean positive affect score (M = 3.18, SD = 0.74) is slightly higher than the negative affect score (M = 2.96, SD = 0.88), indicating a relatively balanced emotional profile within the sample. However, the average anxiety severity score (M = 15.24, SD = 5.12) suggests the presence of mild to moderate anxiety symptoms across the cohort. The observed ranges across all variables demonstrate sufficient variability for predictive modeling and support the suitability of these features for subsequent machine learning analysis [40].

3.1.2. Predictive Model Performance

Four supervised machine learning algorithms were evaluated using 5-fold cross-validation. The Gradient Boosting classifier achieved the highest performance in the integrated multi modal dataset [41].

Table 3. Model Performance Comparison

Model Type	Algorithm	Accuracy	Precision	Recall	F1-Score
Physiological + Behavioral	Random Forest	0.77	0.75	0.73	0.74
Affect Only Logistic Regression	0.80	0.79	0.78	0.78	
Multimodal (P + B + F)	Gradient Boosting	0.88	0.86	0.85	0.85

As shown in Table 3, the comparative evaluation of predictive models indicates that the integrated multimodal approach (Physiological + Behavioral + Affective features) achieved the highest performance across all evaluation metrics. The Gradient Boosting model in the multimodal configuration obtained an accuracy of 0.88, outperforming both the smartwatch-based model (Accuracy = 0.77) and the affect-only model (Accuracy = 0.80). Similar patterns are observed for precision, recall, and F1-score, where the multimodal model consistently demonstrates superior balance between correctly identifying adolescents with anxiety symptoms and minimizing misclassification [42]. The smartwatch-only model shows moderate predictive capability, suggesting that physiological and behavioral indicators alone provide meaningful but incomplete information. Meanwhile, the affect-only model performs slightly better than the smartwatch-only model, highlighting the strong predictive value of subjective emotional states [43]. However, the highest overall performance achieved by the integrated model confirms that combining objective wearable data with subjective affective assessments significantly enhances predictive robustness. These findings empirically support the superiority of multimodal data integration for adolescent anxiety classification [44].

3.1.3. Mediation Analysis

Hierarchical regression analysis revealed:

- Physiological indicators → Affect ($\beta = 0.39$, $p < 0.01$)
- Behavioral indicators → Affect ($\beta = 0.34$, $p < 0.01$)
- Affect → Anxiety ($\beta = 0.56$, $p < 0.001$)

After including affect in the model, the direct effect of smartwatch-derived indicators on anxiety decreased but remained statistically significant, indicating partial mediation. These findings support H3 and confirm the mediating role of affect in the conceptual framework [45].

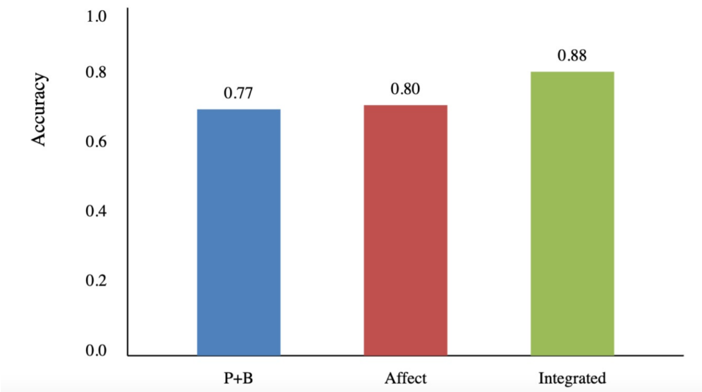

Figure 2. Multimodal Model Accuracy Comparison

As illustrated in Figure 2, the integrated multimodal model achieves the highest prediction accuracy compared to the single-source models. The smartwatch-based model (physiological and behavioral features only) demonstrates moderate predictive performance with an accuracy of 0.77, indicating that wearable-derived objective indicators provide meaningful but limited explanatory power when used independently [46]. The affect-only model performs slightly better, achieving an accuracy of 0.80, highlighting the strong predictive relevance of subjective emotional states in anxiety classification. However, the integrated model that combines physiological, behavioral, and affective features significantly outperforms both single-source approaches, reaching an accuracy of 0.88 [47]. This clear performance improvement visually reinforces the statistical findings presented in Table 3 and confirms that multimodal data integration enhances classification robustness. The comparative difference shown in Figure 2 underscores the added predictive value of combining objective wearable data with subjective affective assessments in adolescent anxiety detection [48, 49].

3.2. Discussion

The findings of this study confirm that integrating objective smartwatch-derived physiological and behavioral indicators with subjective self-reported affect significantly enhances adolescent anxiety prediction within a longitudinal monitoring framework [50, 51]. Lower heart rate variability and reduced sleep duration were consistently associated with higher anxiety severity, supporting autonomic regulation theory which suggests that impaired physiological recovery and emotional regulation are core components of anxiety disorders. Additionally [52, 53], reduced physical activity intensity and lower daily step counts were linked to elevated anxiety levels, aligning with behavioral withdrawal theory that posits anxious adolescents tend to decrease engagement in daily activities. These results highlight the importance of continuous real-world monitoring [54], as wearable technologies are capable of capturing subtle fluctuations in physiological and behavioral patterns that are often missed in episodic clinical assessments [55, 56].

Beyond direct associations, the mediation analysis demonstrates that self-reported affect plays a crucial psychological role in linking smartwatch-derived indicators to anxiety outcomes. The partial mediating effect suggests that physiological dysregulation and behavioral changes influence anxiety not only directly but also indirectly through adolescents' internal emotional experiences [57]. This finding reinforces the theoretical positioning of affect as a central mechanism in anxiety development and underscores the necessity of maintaining a human-centered design in digital mental health systems [58]. While wearable sensors provide scalable and objective data streams, subjective affective assessments remain indispensable for capturing emotional nuances that cannot be fully inferred from biometric signals alone [27, 28].

Furthermore, the superior performance of the integrated multimodal machine learning model compared to single-source models demonstrates the analytical advantage of combining physiological, behavioral, and affective features. The multimodal framework enables the detection of nonlinear and high-dimensional interactions that traditional assessment approaches cannot adequately capture [26]. By adopting a longitudinal and adolescent-focused design, this study extends existing digital mental health research and provides empirical evidence that multimodal integration improves predictive robustness and practical applicability. These findings support the development of scalable, non-invasive anxiety monitoring systems aligned with preventive mental health strategies and broader sustainability goals, particularly SDGs 3 (Good Health and Well-Being) and SDGs 4 (Quality Education) [25, 28].

4. MANAGERIAL IMPLICATIONS

The findings of this study provide important managerial implications for educational institutions, healthcare providers, and digital health system developers. School administrators and education managers can leverage smartwatch-based anxiety prediction systems as an early warning tool to identify students at risk of anxiety without relying solely on self-disclosure or clinical referrals. By integrating predictive insights into school well-being programs, decision-makers can design proactive interventions, such as counseling support, workload adjustments, or targeted mental health initiatives, thereby improving students' emotional well-being and academic engagement in a timely and non-invasive manner.

For healthcare managers and mental health practitioners, the integration of physiological, behavioral, and affective data offers a scalable approach to continuous anxiety monitoring beyond traditional clinical settings. Wearable-enabled predictive models allow practitioners to prioritize at-risk adolescents, optimize resource allocation, and deliver personalized preventive interventions rather than reactive treatments. This data-driven approach supports more efficient mental health service management and aligns with preventive healthcare strategies emphasized in adolescent mental health policies.

From a technology management perspective, the results highlight the importance of adopting a human-centered design in digital mental health solutions. Developers and system managers should prioritize multimodal data integration, interpretability of predictive outputs, and ethical data governance, including privacy protection and informed consent. By embedding these considerations into system design and implementation, organizations can enhance user trust, ensure responsible use of wearable data, and support the sustainable deployment of anxiety prediction technologies aligned with long-term educational and healthcare objectives.

5. CONCLUSION

This study addresses an important research gap in adolescent mental health monitoring by developing an anxiety prediction model that integrates smartwatch-derived physiological and behavioral data with self-reported affect scales. While previous studies have predominantly focused on adult populations or relied on single-source data, this research extends existing knowledge by adopting a longitudinal, multimodal approach tailored specifically to adolescents. The findings demonstrate that combining objective wearable sensor data with subjective affective assessments provides a more comprehensive representation of anxiety, enabling more accurate and continuous detection compared to conventional assessment methods.

The novelty of this study lies in its human-centered integration of multimodal data within a machine learning framework for adolescent anxiety prediction. By positioning self-reported affect as a mediating construct between smartwatch activity indicators and anxiety outcomes, the proposed model captures both observable behavioral patterns and internal emotional experiences. This approach not only improves predictive performance but also ensures that technological solutions remain sensitive to adolescents' psychological contexts, aligning wearable-based analytics with preventive mental health objectives and sustainable digital health principles.

Despite its contributions, this study opens several avenues for future research. Subsequent studies may incorporate larger and more diverse adolescent populations to enhance model generalizability across cultural and socio-economic contexts. Future research could also explore the integration of additional data sources, such as contextual, academic, or social interaction data, as well as the application of explainable artificial intelligence techniques to improve model transparency and clinical interpretability. Long-term intervention studies are further recommended to evaluate how real-time anxiety prediction systems influence behavioral change, mental health outcomes, and educational performance over extended periods.

6. DECLARATIONS

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6.2. Author Contributions

Conceptualization: SV; Methodology: MF; Software: PA; Validation: RS and NA; Formal Analysis: RS and SV; Investigation: NA; Resources: MF; Data Curation: LP; Writing Original Draft Preparation: NP and MR; Writing Review and Editing: NR and MM; Visualization: NA; All authors, PA, MF, NA, SV, and RS, have read and agreed to the published version of the manuscript.

6.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] L. Lutz, P. Veltmann, R. Meisterhans, and M. Giurgiu, "Associations between wearables vital parameters and self-perceived mood—an ecological momentary assessment study among healthy adolescents," *Frontiers in Psychology*, vol. 16, p. 1623886, 2025.

[2] Department of Health and Social Care, "Mental health and wellbeing plan: Discussion paper and call for evidence," Department of Health and Social Care, United Kingdom, Tech. Rep., Apr 2022. [Online]. Available: https://www.gov.uk/government/calls-for-evidence/mental-health-and-wellbeing-plan-discussion-paper-and-call-for-evidence/mental-health-and-wellbeing-plan-discussion-paper

[3] U. Rahardja, L. Sulistyo, D. Safarina, M. R. Kusuma, N. Silawati, and Z. Nanle, "Hibahqu education monitoring platform based on human-centric orange technology laravel 12 vue. js," *ADI Bisnis Digital Interdisiplin Jurnal*, vol. 6, no. 2, pp. 203–218, 2025.

[4] Y. T. Jo, S. W. Lee, S. Park, and J. Lee, "Association between heart rate variability metrics from a smartwatch and self-reported depression and anxiety symptoms: a four-week longitudinal study," *Frontiers in Psychiatry*, vol. 15, p. 1371946, 2024.

[5] B. Saylam and Ö. D. İncel, "Quantifying digital biomarkers for well-being: stress, anxiety, positive and negative affect via wearable devices and their time-based predictions," *Sensors*, vol. 23, no. 21, p. 8987, 2023.

[6] K. Diantoro, M. P. Hannah, M. Wali, I. Sutedja, N. Silawati *et al.*, "Optimizing federated learning efficiency for real-time online course applications," in *2025 4th International Conference on Creative Communication and Innovative Technology (ICCIT)*. IEEE, 2025, pp. 1–7.

[7] E. Zhang, M. Clark, and A. Doryab, "Predicting the severity of anxiety in adolescents through passively sensed behaviors," in *Proceedings of the ACM/IEEE International Conference on Connected Health: Applications, Systems and Engineering Technologies*, 2025, pp. 81–92.

[8] Y.-B. Shin, A. Y. Kim, S. Kim, M.-S. Shin, J. Choi, K. L. Lee, J. Lee, S. Byun, S. Kim, H.-J. Lee *et al.*, "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*, vol. 15, no. 6, p. e096773, 2025.

[9] A. Velu, J. Ramesh, A. Ahmed, S. Ganguly, R. Aburukba, A. Sagahyroon, and F. Aloul, "Integrating fitbit wearables and self-reported surveys for machine learning-based state–trait anxiety prediction," *Applied Sciences*, vol. 15, no. 19, p. 10519, 2025.

[10] C. Nadal, C. Earley, A. Enrique, C. Sas, D. Richards, and G. Doherty, "Patient acceptance of self-monitoring on a smartwatch in a routine digital therapy: a mixed-methods study," *ACM Transactions on Computer-Human Interaction*, vol. 31, no. 1, pp. 1–50, 2023.

[11] D. S. S. Wuisan, R. A. Sunardjo, Q. Aini, N. A. Yusuf, and U. Rahardja, "Integrating artificial intelligence in human resource management: A smartpls approach for entrepreneurial success," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 5, no. 3, pp. 334–345, 2023.

[12] E. Kalisperakis, T. Karantinos, M. Lazaridi, V. Garyfalli, P. P. Filntisis, A. Zlatintsi, N. Efthymiou, A. Mantas, L. Mantonakis, T. Mougiakos *et al.*, "Smartwatch digital phenotypes predict positive and negative symptom variation in a longitudinal monitoring study of patients with psychotic disorders," *Frontiers in Psychiatry*, vol. 14, p. 1024965, 2023.

[13] Y.-R. Lee and J.-S. Lee, "Real-time monitoring to predict depressive symptoms: study protocol," *Frontiers in Psychiatry*, vol. 15, p. 1465933, 2025.

[14] E. Setiawaty, H. Hartoyo, R. Nurmalina, and L. N. Yuliati, "Entrepreneurship and innovation in telemedicine adoption among physicians in indonesia," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 3, pp. 927–941, 2025.

[15] S. Sumińska and A. Rynkiewicz, "Mindfulness-based stress reduction training supplemented with physiological signals from smartwatch improves mindfulness and reduces stress, but not anxiety and depression," *Plos one*, vol. 20, no. 4, p. e0322413, 2025.

[16] P. Lialiou and I. Maglogiannis, "Students' burnout symptoms detection using smartwatch wearable devices: a systematic literature review," *AI Sensors*, vol. 1, no. 1, p. 2, 2025.

[17] N. Lutfiani, D. A. Astrieta, V. Wildan, H. Sulistyaningrum, M. R. Anwar, and E. D. Astuti, "Emotional well-being and psychological support in infertility a multi-modal ai approach," *International Journal of Cyber and IT Service Management (IJCITSM)*, vol. 5, no. 1, pp. 81–92, 2025.

[18] T. Robinson, J. Condell, E. Ramsey, and G. Leavey, "Self-management of subclinical common mental health disorders (anxiety, depression and sleep disorders) using wearable devices," *International journal of environmental research and public health*, vol. 20, no. 3, p. 2636, 2023.

[19] N. K. Sahu, S. Gupta, and H. R. Lone, "Mad: A multimodal physiological and self-reported dataset for anxiety research from a low-to-middle-income country," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 9, no. 4, pp. 1–34, 2025.

[20] K. V. Olesen, N. N. Lønfeldt, S. Das, A. K. Pagsberg, and L. K. H. Clemmensen, "Predicting obsessive-compulsive disorder events in children and adolescents in the wild using a wearable biosensor (wrist angel): Protocol for the analysis plan of a nonrandomized pilot study," *JMIR research protocols*, vol. 12, no. 1, p. e48571, 2023.

[21] L. Meria, A. Andriyansah, F. Sutisna, A. William, and L. Pasha, "Unveiling the role of smartpls and technology in analyzing hr dynamics for organizational effectiveness," *International Journal of Cyber and IT Service Management (IJCITSM)*, vol. 5, no. 1, pp. 71–80, 2025.

[22] G. C. Malave, "Digital health and wearable technologies for the diagnosis and management of suicidality in adolescents and young adults: A scoping review," Master's thesis, College of Medicine-Mayo Clinic, 2023.

[23] L. Marciano, E. Vocaj, M. A. Bekalu, A. La Tona, G. Rocchi, and K. Viswanath, "The use of mobile assessments for monitoring mental health in youth: Umbrella review," *Journal of Medical Internet Research*, vol. 25, p. e45540, 2023.

[24] J. L. Borelli, Y. Wang, F. H. Li, L. N. Russo, M. Tironi, K. Yamashita, E. Zhou, J. Lai, B. Nguyen, I. Azimi

et al., “Detection of depressive symptoms in college students using multimodal passive sensing data and light gradient boosting machine: longitudinal pilot study,” *JMIR Formative Research*, vol. 9, no. 1, p. e67964, 2025.

[25] M. Choiri, E. S. Pramudito, F. Sutisna, and R. S. Sean, “Business artificial intelligence for enhancing sustainable decision intelligence,” *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 7, no. 1, pp. 106–116, 2025.

[26] A. Sameh, L. Nauha, M. Seppänen, M. Niemelä, M. Oussalah, R. Korpelainen, and V. Farrahi, “Digital phenotyping using wearable-determined physical behaviors and machine learning to detect depression and anxiety in a general population,” *medRxiv*, pp. 2025–09, 2025.

[27] N. Kwon, D. Lee, S. Hwang, S. Yang, I. Youn, H.-J. Moon, and S. Han, “Enhancing the accuracy of mental health assessments through the integration of self-report and objective measures: A convergence study utilizing biosignals and 14-day wearable data,” *Acta Psychologica*, vol. 259, p. 105432, 2025.

[28] E. Erika, B. S. Riza, S. Maulana, and S. Rahagi, “Mapping the nexus of strategic management and sustainable development goals 12 with a focus on innovation: A bibliometric analysis,” *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 7, no. 1, pp. 71–84, 2025.

[29] S. Yokoyama, F. Kagawa, M. Takamura, K. Takagaki, K. Kambara, Y. Mitsuyama, A. Shimizu, G. Okada, and Y. Okamoto, “Day-to-day regularity and diurnal switching of physical activity reduce depression-related behaviors: a time-series analysis of wearable device data,” *BMC public health*, vol. 23, no. 1, p. 34, 2023.

[30] A. Horwitz, E. Czyz, N. Al-Dajani, W. Dempsey, Z. Zhao, I. Nahum-Shani, and S. Sen, “Utilizing daily mood diaries and wearable sensor data to predict depression and suicidal ideation among medical interns,” *Journal of affective disorders*, vol. 313, pp. 1–7, 2022.

[31] H. W. Jung, D. Y. Kim, I. Lee, O. Kim, S. Lee, S. Lee, U. S. Chung, J.-H. Kim, S. Kim, J. W. Kim *et al.*, “Key features of digital phenotyping for monitoring mental disorders: Systematic review,” *Journal of Medical Internet Research*, vol. 27, p. e77331, 2025.

[32] A. Williams, Y. Hasudungan, and N. Azizah, “The implementation of effective financial management to increase the profitability of startups,” *Startupreneur Business Digital (SABDA Journal)*, vol. 4, no. 1, pp. 47–54, 2025.

[33] R. Tutunji, R. Proppert, C. Rieble, N. Jacobson, and E. Fried, “Integrating ecological momentary and passive sensing data to improve depression severity prediction: Insights from the warn-d study,” 2025.

[34] S. Fazeli, L. Levine, M. Beikzadeh, B. Mirzasoleiman, B. Zadeh, T. Peris, and M. Sarrafzadeh, “Passive monitoring of physiological precursors of stress leveraging smartwatch data,” in *2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. IEEE, 2022, pp. 2893–2899.

[35] B. Saylam and Ö. D. İncel, “Multitask learning for mental health: depression, anxiety, stress (das) using wearables,” *Diagnostics*, vol. 14, no. 5, p. 501, 2024.

[36] Q. Aini, M. Hardini, A. Faturahman, D. Apriliasari, and A. C. Kiboy, “Analyzing user acceptance of ai based water quality monitoring through the utaut2 framework,” *Sundara Advanced Research on Artificial Intelligence*, vol. 1, no. 2, pp. 65–73, 2025.

[37] A. Arora, P. Chakraborty, and M. Bhatia, “Intervention of wearables and smartphones in real time monitoring of sleep and behavioral health: an assessment using adaptive neuro-fuzzy technique,” *Arabian Journal for Science and Engineering*, vol. 47, no. 2, pp. 1999–2024, 2022.

[38] R. V. Shah, G. Grennan, M. Zafar-Khan, F. Alim, S. Dey, D. Ramanathan, and J. Mishra, “Personalized machine learning of depressed mood using wearables,” *Translational psychiatry*, vol. 11, no. 1, p. 338, 2021.

[39] A. Abudaqa and I. Noburu, “Optimizing digipreneurship in the growth of the digital millennial creative economy ecosystem,” *Startupreneur Business Digital (SABDA Journal)*, vol. 4, no. 1, pp. 24–34, 2025.

[40] A. Ahmed, S. Aziz, M. Alzubaidi, J. Schneider, S. Irshaidat, H. A. Serhan, A. A. Abd-Alrazaq, B. Solaiman, and M. Househ, “Wearable devices for anxiety & depression: A scoping review,” *Computer Methods and Programs in Biomedicine Update*, vol. 3, p. 100095, 2023.

[41] N. K. Sahu, S. Gupta, and H. Lone, “Wearable technology insights: Unveiling physiological responses during three different socially anxious activities,” *ACM Journal on Computing and Sustainable Societies*, vol. 2, no. 2, pp. 1–23, 2024.

[42] S. Jafarlou, I. Azimi, J. Lai, Y. Wang, S. Labbaf, B. Nguyen, H. Qureshi, C. Marcotullio, J. L. Borelli, N. D. Dutt *et al.*, “Objective monitoring of loneliness levels using smart devices: A multi-device approach

for mental health applications," *Plos one*, vol. 19, no. 6, p. e0298949, 2024.

[43] Y.-B. Shin, A. Y. Kim, S. Kim, M.-S. Shin, J. Choi, K. L. Lee, J. Lee, S. Byun, S. Kim, and H.-J. Lee, "Development of Prediction Models for Screening Depression and Anxiety Using Smartphone and Wearable-Based Digital Phenotyping," *BMJ Open*, vol. 15, no. 6, p. e096773, 2025.

[44] Y. Koh, C. Lee, E. Joung, H. Lee, and U. Lee, "Harnessing Home IoT for Self-Tracking Emotional Well-Being: Behavioral Patterns, Self-Reflection, and Privacy Concerns," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 9, no. 3, pp. 1–36, 2025.

[45] R. Amin, S. Schreynemackers, H. Oppenheimer, M. Petrovic, U. Hegerl, and H. Reich, "Mobile Sensing Data for Longitudinal Monitoring and Prediction of Depression Severity: A Systematic Review," *J Med Internet Res*, vol. 27, p. e57418, 2025.

[46] E. A. Ankrah, F. L. Cibrian, L. M. Silva, A. Tavakoulnia, J. A. Beltran, S. E. B. Schuck, K. D. Lakes, and G. R. Hayes, "Me, My Health, and My Watch: How Children With ADHD Understand Smartwatch Health Data," *ACM Trans. Comput.-Hum. Interact.*, vol. 30, no. 4, pp. 1–25, 2023.

[47] M. M. Rahman, "Unlocking the Potential of Wearable Technology: Fitbit-Derived Measures for Predicting ADHD in Adolescents," *Front Child Adolesc Psychiatry*, vol. 4, p. 1504323, 2025.

[48] D. Yamin, S. Lev-Ari, M. Mofaz, R. Elias, S. Toker, D. Spiegel, M. Yechezkel, M. L. Brandeau, and E. Shmueli, "Social Media Impact and Smartwatch Monitoring: Early Markers of PTSD and Anxiety Following Mass Traumatic Events," *PLOS Ment Health*, vol. 2, no. 9, p. e0000195, 2025.

[49] J. Um, J. Park, D. E. Lee, J. E. Ahn, and J. H. Baek, "Machine Learning Models to Identify Imminent Suicide Risk Using Wearable Devices: A Pilot Study," *Psychiatry Investig*, vol. 22, no. 2, p. 156, 2025.

[50] A. Abd-Alrazaq, R. AlSaad, S. Aziz, A. Ahmed, K. Denecke, M. Househ, F. Farooq, and J. Sheikh, "Wearable Artificial Intelligence for Anxiety and Depression: A Scoping Review," *J Med Internet Res*, vol. 25, p. e42672, 2023.

[51] Y.-B. Shin, A. Y. Kim, S. Kim, M.-S. Shin, J. Choi, K. L. Lee, J. Lee, S. Byun, S. Kim, and H.-J. Lee, "Development of prediction models for screening depression and anxiety using smartphone and wearable-based digital phenotyping," *BMJ Open*, vol. 15, no. 6, p. e096773, 2025.

[52] Y. Koh, C. Lee, E. Joung, H. Lee, and U. Lee, "Harnessing home iot for self-tracking emotional wellbeing: behavioral patterns and privacy concerns," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 9, no. 3, pp. 1–36, 2025.

[53] R. Amin, S. Schreynemackers, H. Oppenheimer, M. Petrovic, U. Hegerl, and H. Reich, "Use of mobile sensing data for longitudinal monitoring and prediction of depression severity: systematic review," *Journal of Medical Internet Research*, vol. 27, p. e57418, 2025.

[54] E. A. Ankrah, F. L. Cibrian, L. M. Silva, A. Tavakoulnia, J. A. Beltran, S. E. B. Schuck, K. D. Lakes, and G. R. Hayes, "How children with adhd interpret smartwatch health data," *ACM Transactions on Computer-Human Interaction*, vol. 30, no. 4, pp. 1–25, 2023.

[55] A. Abd-Alrazaq, R. AlSaad, S. Aziz, A. Ahmed, K. Denecke, M. Househ, F. Farooq, and J. Sheikh, "Wearable artificial intelligence for anxiety and depression: scoping review," *Journal of Medical Internet Research*, vol. 25, p. e42672, 2023.

[56] A. Choi, A. Ooi, and D. Lottridge, "Digital phenotyping for stress, anxiety, and mild depression: a systematic literature review," *JMIR mHealth and uHealth*, vol. 12, no. 1, p. e40689, 2024.

[57] A. Kargarandehkordi, S. Li, K. Lin, K. T. Phillips, R. M. Benzo, and P. Washington, "Fusing wearable biosensors with artificial intelligence for mental health monitoring: a systematic review," *Biosensors*, vol. 15, no. 4, p. 202, 2025.

[58] R. P. Hirten, M. Suprun, M. Danieletto, M. Zweig, E. Golden, R. Pyzik, S. Kaur, D. Helmus, A. Biello, and K. Landell, "Machine learning approach to determine resilience utilizing wearable device data," *JAMIA Open*, vol. 6, no. 2, p. ooad029, 2023.