Journal of Engineering and Technology

ISSN 2180-3811 eISSN 2289-814X https://jet.utem.edu.my/jet/index

DOI: https://doi.org/10.54554/jet.2025.16.2.015

RESEARCH ON THE TECHNICAL FRAMEWORK OF WEARABLE INTERNET OF THINGS DEVICES IN MENTAL HEALTH SOCIAL WORK INTERVENTIONS

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Article history:

Received Date: 20 Jun 2025

Revised Date: 28 July 2025

Accepted Date: 8 August 2025

Keywords: Digital Health Interventions, Machine

Abstract— Mental health disorders impact an estimated 500 million individuals globally, yet conventional service delivery models encounter considerable challenges, including geographic constraints, limited accessibility, and suboptimal resource distribution. This study introduces a comprehensive technical framework that integrates wearable Internet of Things (IoT) devices with social work interventions to enhance mental health care delivery. Employing a mixed-methods research

Learning, Mental Health Social Work, Physiological Monitoring, Wearable IoT Devices	design, the investigation involved 240 participants, allocated into experimental and control groups, over a 12-week duration. The proposed system architecture consists of four layers: data collection, data processing, decision-making algorithms, and evaluation display. It utilizes a range of wearable sensors, such as smartwatches, health bracelets, and physiological monitoring devices. Machine learning analyses yielded an overall accuracy of 89.3%, with convolutional neural network (CNN) models achieving 92% accuracy in analysing multidimensional time series data. The results reveal significant correlations between physiological metrics and mental health status (correlation coefficients ranging from 0.55 to 0.81), with heart rate variability exhibiting the strongest association with stress indices (r = 0.81). Post-intervention assessments demonstrated notable improvements on standardized mental health measures, with effect sizes surpassing Cohen's d = 0.8. The framework effectively facilitates real-time alerts, personalized recommendations, peer support, and access to professional consultation. User acceptance analysis indicated high satisfaction concerning convenience and individualized service experiences, although privacy concerns were identified as areas necessitating further attention.

I. Introduction

Mental health disorders represent a critical global public health issue, impacting an estimated 500 million individuals worldwide, with depression, schizophrenia, and dementia identified as the most prevalent conditions [1]. Traditional models of mental health service delivery primarily depend on face-to-face clinical assessments and interventions. However, these models are constrained by several limitations, including geographic barriers, limited accessibility to services, social stigma, and uneven distribution of resources [2].

The rapid development of Internet of Things (IoT) technologies presents transformative opportunities for the field of mental health care. Wearable IoT devices enable continuous monitoring of physiological and behavioural indicators such as heart rate, sleep patterns, physical activity, and skin conductance that are closely associated with mental health conditions. Recent studies demonstrate that wearable devices can attain accuracy rates of 85-90% in mental health monitoring, thereby facilitating personalized, real-time feedback [3].

The social work profession plays a vital role in mental health services by delivering psychosocial assessments, case management, crisis intervention, and community rehabilitation. Nonetheless, conventional social work practice models encounter challenges including workforce shortages, excessive caseloads, and a lack of real-time informational support. Consequently, the integration of technology has become increasingly essential in modern social work practice, particularly in the post-pandemic era, which has seen a substantial rise in demand for remote services and digital health tools.

II. Literature Review

Existing scholarship has affirmed the promising role of wearable devices in the monitoring of mental health. For instance, researchers at Washington University developed the WearNet deep learning framework, which analysed data collected from over 10,000 Fitbit users. This model demonstrated superior accuracy relative to conventional machine learning techniques in detecting symptoms of depression and anxiety [4]. Further investigations have revealed that physiological indicators such as heart rate variability, sleep patterns, and physical activity metrics derived from wearable technology can serve as reliable predictors of fluctuations in mental health status [5].

Within the domain of artificial intelligence, convolutional neural networks (CNNs) have shown optimal performance in processing multidimensional time-series data obtained from wearable devices, achieving accuracy rates ranging from 89% to 92%. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) architectures, have consistently demonstrated robust capabilities in long-term predictive modelling. In contrast, support vector machines (SVMs) have exhibited comparatively lower efficacy when applied to the large-scale datasets generated by wearable technologies [6-7].

Research on the integration of technology within social work has predominantly concentrated on telemedicine, case management software, and digital intervention platforms. The COVID-19 pandemic notably accelerated the adoption of digital tools among social workers, including teletherapy, virtual counselling, and online support groups. Empirical evidence suggests that technology-assisted mental health interventions can, in certain contexts, produce outcomes comparable to those achieved through traditional treatment approaches [8].

III. Research Objectives

The present study seeks to develop a comprehensive framework for the integration of wearable IoT technology to augment social work interventions within the domain of mental health. The specific objectives include:

i) Designing an end-to-end system architecture that incorporates data acquisition, processing, decision-making algorithms, and evaluation interfaces.

ii) Assessing the accuracy and efficacy of the system in monitoring mental health and facilitating interventions.
iii) Investigating the practical feasibility and user acceptance of the proposed system in real-world applications.
iv) Formulating guidelines to address ethical considerations and ensure the protection of user privacy.

IV. Research Hypotheses

H1: There exist significant correlations between physiological metrics obtained via wearable IoT devices and individuals' mental health status.

H2: The implementation of the integrated technological framework significantly enhances the effectiveness of social work interventions targeting mental health.

H3: End-users exhibit high levels of acceptance and satisfaction with the deployed technology framework.

V. Research Methodology

A. Research Design

This investigation adopts a mixed-methods approach, combining quantitative experimental research with qualitative case study analysis. The study is organized into three sequential phases: system development, experimental validation, and impact assessment.

B. Technical Architecture

The system architecture is composed of four principal layers:

i) Data Collection Layer: Utilizes a range of wearable sensors and smart devices to gather data.
ii) Data Processing Layer: Encompasses procedures for data cleaning, feature extraction, and preprocessing.
iii) Decision Algorithm Layer: Employs machine learning and artificial intelligence techniques to analyse health status.
iv) Evaluation and Display Layer: Facilitates user interface interactions and decision support functionalities.

Hardware Component Selection

Drawing upon a comprehensive literature review and expert consultations, the following wearable devices were chosen and summarized in Table 1.

i) Smart Watch: Monitors heart rate, heart rate variability, and physical activity levels.
ii) Health Bracelet: Records sleep patterns, step counts, and caloric expenditure.
iii) Smart Ring: Measures skin conductance and fluctuations in body temperature.
iv) Physiological Sensors: Track respiratory rate and blood oxygen saturation levels.

Software Architecture Utilizes

The system architecture integrates cloud computing with edge computing technologies to optimize performance and data processing. Apache Kafka is utilized for real-time streaming and processing of data flows, while MongoDB serves as the database for storing unstructured health-related data. The analytical framework incorporates multiple machine learning algorithms, including CNN, LSTM, Random Forest, and SVM.

Table 1: Comparison of Performance of Wearable IoT Devices

Device Type	Accuracy	User Satisfaction	Battery Life (hours)
Smart Watch	0.92	4.3	72
Health Band	0.89	4.1	168
Smart Ring	0.85	3.8	96
Physiological Sensor	0.94	4.5	48
Heart Rate Patch	0.91	4.2	120

C. Research Participants

Inclusion Criteria

i) Adults aged between 18 and 65 years.
ii) Individuals experiencing mild to moderate symptoms of mental health distress, such as depression, anxiety, or stress.
iii) Willingness to engage with wearable technology and participate in the study protocol.
iv) Basic proficiency in technology use.

Exclusion Criteria

i) Individuals diagnosed with severe mental disorders necessitating hospitalization.
ii) Pregnant or lactating women.

iii) Persons with medical implants, such as pacemakers.
iv) Participants unable to comprehend study materials or who decline to provide informed consent.

Sample Size Determination

Sample size was calculated based on Cohen's effect size formula, with a significance level (α) of 0.05, statistical power of 0.80, and an anticipated medium effect size (d = 0.5). This calculation indicated a requirement of 64 participants per group. To accommodate an estimated attrition rate of 20%, the final sample size was adjusted to 120 participants per group, resulting in a total of 240 participants. The demographic characteristics of participants is shown in Table 2.

Table 2: Demographic Characteristics of Participants

Participant Characteristics	Experimental Group (n=120)	Control Group (n=120)	*p*-value
Age (mean ± SD)	34.2 ± 8.5	33.8 ± 9.1	0.725
Gender (Male/Female)	52 / 68	49 / 66	0.831
Education Level (University or above)	89 (74.2%)	85 (73.9%)	0.951
History of Mental Health Issues	23 (19.2%)	21 (18.3%)	0.877
Technology Usage Experience	4.1 ± 0.8	4.0 ± 0.9	0.342

D. Data Collection

Physiological Data

Participants were instructed to continuously wear wearable devices over a 12-week period to collect physiological indicators, including heart rate variability, sleep quality metrics, physical activity levels, skin conductance responses, and fluctuations in body temperature.

Mental Health Assessment

Standardized psychometric instruments were administered biweekly, comprising the Beck Depression Inventory, Beck Anxiety Inventory, Perceived Stress Scale, and the World Health Organization Quality of Life Scale.

E. Intervention Program

The system delivers personalized intervention strategies, which include:

i) Real-time alerts triggered by abnormal physiological parameters.
ii) Customized recommendations derived from individual health data profiles.
iii) Facilitation of peer support networks connecting users with similar experiences.
iv) Provision of remote consultations with licensed social workers.
v) Monitoring of behavioural changes with corresponding feedback mechanisms.

F. Data Analysis Methods

Quantitative Analysis

Statistical analyses were conducted using SPSS version 28.0 and Python. Methods included descriptive statistics, correlation analyses, independent t-tests, repeated measures ANOVA, and calculation of effect sizes.

Machine Learning Model Evaluation

Performance of machine learning models was evaluated using metrics such as accuracy, sensitivity, specificity, *F1* score, and the area under the receiver operating characteristic curve (AUC-ROC).

Qualitative Analysis

Interview data were subjected to thematic analysis, involving transcription, initial coding, identification and classification of themes, analysis of inter-theme relationships, and validation of interpretative findings.

VI. Results and Discussion

A. Principal Research Outcomes

Correlation between Physiological Metrics and Mental Health Status

This study establishes a significant correlation between physiological indicators obtained from wearable Internet of Things devices and mental health status, thereby validating hypothesis H1. Analysis results as tabulated in Table 3 reveals that the correlation coefficient between heart rate variability and the stress index is the highest at r=0.81, followed by correlations with depressive symptoms at r=0.73

and anxiety symptoms at r=0.76.

These findings align with the results of the WearNet study conducted at Washington University, which similarly demonstrated that data from wearable devices can effectively predict mental health status [4]. Heart rate variability, as an indicator of autonomic nervous system function, underscores the significance of the mind-body connection due to its strong correlation with mental health outcomes.

Table 3: Correlation Analysis of Physiological Indicators and Mental Health Status

Physiological Indicator	Correlation with Depression	Correlation with Anxiety	Correlation with Stress Index
Heart Rate Variability	0.73	0.76	0.81
Sleep Quality	0.68	0.62	0.74
Activity Level	0.71	0.59	0.66
Skin Conductance	0.65	0.72	0.78
Body Temperature Change	0.58	0.55	0.62

Furthermore, the robust association between sleep quality and mental health, with correlation coefficients ranging from r=0.68 to r=0.74, corroborates existing literature that emphasizes the close relationship between sleep disorders and symptoms of depression and anxiety. Additionally, data on activity levels indicates a higher correlation with depressive symptoms (r=0.71), thereby reinforcing the importance of exercise therapy in the treatment of depression.

Performance of the Technical Architecture

The integrated technological framework established in this research exhibits exceptional efficacy in the monitoring and intervention of mental health. The machine learning models achieved an overall accuracy of 89.3%, with the CNN model demonstrating superior performance in managing multidimensional time series data, attaining an accuracy of 92%. Additionally, the LSTM model exhibited commendable stability in forecasting long-term trends.

The system's capacity for real-time response aligned with the anticipated objectives, achieving an average data processing delay of under 2s, thereby fulfilling the immediate alert requirements during emergencies. Furthermore, the cloud-edge hybrid computing architecture successfully minimized data transmission load while maintaining data security.

Evaluation of Intervention Effects

The experimental results as shown in Table 4 provide strong support for hypothesis H2, indicating that the integrated technical architecture markedly enhances the effectiveness of social work interventions in mental health. All standardized assessment scales reveal significant improvements in the experimental group post-intervention, with effect sizes reaching substantial levels (Cohen's $d > 0.8$).

Table 4: Changes in Mental Health Indicators Before and After Wearable IoT Intervention

Assessment Scale	Pre-intervention (Mean ± SD)	Post-intervention (Mean ± SD)	Effect Size (Cohen's d)	*p*-value
Beck Depression Inventory (BDI-II)	24.3 ± 6.2	16.5 ± 5.8	1.32	<0.001
Beck Anxiety Inventory (BAI)	18.7 ± 5.1	12.4 ± 4.6	1.31	<0.001
Perceived Stress Scale (PSS)	26.8 ± 4.9	19.2 ± 4.2	1.67	<0.001
Quality of Life Scale (WHOQOL)	52.1 ± 8.3	68.3 ± 7.9	2.03	<0.001
Global Assessment of Functioning (GAF)	64.2 ± 9.1	78.6 ± 8.4	1.68	<0.001

The most pronounced improvement is observed in the quality of life scale (d=2.03), suggesting that the wearable IoT intervention not only alleviates specific symptoms but also significantly enhances overall quality of life.

B. Innovations and Key Contributions

Technological Advancements

The primary technological advancement presented in this study is the development of the inaugural integrated wearable IoT framework tailored specifically to address the practical requirements of mental health social work. In contrast to existing research, this framework considers the distinctive needs of the social work profession, incorporating modules for case management, crisis intervention, and community support.

Additionally, the implementation of hybrid machine learning algorithms represents a noteworthy innovation. This study is pioneering in its organic integration of CNN, LSTM and Random Forest algorithms, thereby ensuring both predictive accuracy and interpretability, which are essential for informed decision-making within the social work field.

Innovations in Practical Application

The personalized intervention strategies formulated in this research encompass five distinct intervention methods as shown in Table 5. Qualitative analysis indicates that “professional consultation” achieved the highest effectiveness rating (4.5), albeit with the greatest implementation difficulty (4.1). Conversely, “real-time alerts” and “behaviour tracking” exhibit lower implementation challenges while still demonstrating commendable effectiveness.

Table 5: Effectiveness Assessment of Various Intervention Methods

Intervention Method	Effectiveness Rating	Implementation Difficulty
Real-time Alerts	3.8	2.1
Personalized Suggestions	4.2	3.2
Peer Support	3.9	3.8
Professional Consultation	4.5	4.1
Behaviour Tracking	4.0	2.5

C. User Acceptance and Satisfaction

The findings from the qualitative research provide robust support for hypothesis H3, demonstrating that users exhibit a high degree of acceptance and satisfaction with the technological framework. The thematic analysis has revealed four primary themes.

Convenience and Accessibility

Participants generally perceive wearable devices as offering unparalleled convenience, particularly for individuals residing in remote locations or those experiencing mobility challenges. One participant remarked, *"I can receive professional health monitoring at home, which is very important to me."*

Personalized Service Experience

Users place significant value on the personalized recommendations and intervention strategies offered by the system. Numerous participants indicated that tailored health advice is more compelling and applicable than generic health information.

Privacy and Security Concerns

Despite the overall high levels of satisfaction, some participants voiced concerns regarding privacy and security. This underscores the necessity of enhancing privacy protection measures throughout the technological development process.

Professional Role of Social Workers

Participants from the social work profession expressed appreciation for the system's ability to support their professional judgment rather than replace it. They believe that technological tools serve to augment their professional capabilities rather than undermine their professional standing.

VII. Conclusions and Future Directions

A. Principal Findings

This research successfully developed and validated a comprehensive wearable IoT technology framework, substantiating three core hypotheses. The observed correlation coefficients between physiological metrics and mental health status ranged from 0.55 to 0.81. Furthermore, all assessed mental health indicators exhibited statistically significant improvements, with effect sizes indicating substantial impact.

B. Theoretical Contributions

A novel theoretical model was formulated, elucidating the relationship between wearable IoT-derived data and mental health status, thereby affirming the applicability of ecosystem theory within the context of the digital age. The integration of hybrid machine learning algorithms facilitated a balance between predictive accuracy and model interpretability.

C. Practical Contributions

This study provides a scientifically grounded decision support system tailored for mental health social work, markedly improving service accessibility, especially for populations in remote or underserved regions. The personalized intervention framework, which synthesizes five distinct methodologies, demonstrated superior efficacy compared to single-method interventions.

D. Societal Implications

The findings advance health equity by enhancing access to mental health services among marginalized communities. Additionally, the research supports a paradigm shift from treatment-centric to prevention-focused approaches, enabling timely interventions through continuous monitoring and early warning mechanisms.

E. Limitations and Future Research Directions

The sample predominantly comprised urban participants, and the study’s temporal scope was limited. Future research should prioritize longitudinal follow-up studies, cross-cultural validation, and comprehensive cost-effectiveness evaluations. Technological development efforts should emphasize improvements in accuracy, intelligence, and user experience, underscoring the necessity for governmental policy initiatives to facilitate widespread adoption and implementation.

VIII. References

[1] A. J. Mitchell, I. E. Cogswell, J. Dalos, G. Tsakalos, J. Lei, A. Oros, and A. E. Apeagyei, “Estimating global direct health-care spending on neurological and mental health between 2000 and 2019: a modelling study,” *The Lancet Public Health*, vol. 10, no. 5, pp. e401-e411, 2025.

[2] F. Atewologun, O. A. Adigun, O. J. Okesanya, H. K. Hassan, O. N. Olabode, A. S. Micheal, and D. E. Lucero-Prisno, “A comprehensive review of mental health services across selected countries in sub-Saharan Africa: assessing progress, challenges, and future direction,” *Discover mental health*, vol. 5, no. 1, pp. 1-19, 2025.

[3] N. Gomes, M. Pato, A. R. Lourenco and N. Datia, “A survey on wearable sensors for mental health monitoring,” *Sensors*, vol. 23, no. 3, p. 1330, 2023.

[4] R. Dai, T. Kannampallil, S. Kim, V. Thornton, L. Bierut, and C. Lu, “Detecting mental disorders with wearables: A large cohort study,” in *Proceedings of the 8th ACM/IEEE Conference on Internet of Things Design and Implementation*, May 2023, pp. 39-51.

[5] W. Zhao and K. Go, “Wearable Sensors and Machine Learning: Insights into Depression, Anxiety, and Emotional States and Changes,” in *2025 International Conference on Computing, Networking and Communications (ICNC)*, 2025, pp. 145-150.

[6] S. Mehta and S. Kaur, “Hybrid CNN-SVM Approach for Time-Series Activity Recognition Using Wearable Sensors,” in *2025 International Conference on Automation and Computation (AUTOCOM)*, 2025, pp. 1432-1436.

[7] M. Z. Arshad, A. Jamsrandorj, J. Kim, and K. R. Mun, “Gait events prediction using hybrid CNN-RNN-based deep learning models through a single waist-worn wearable sensor,” *Sensors*, vol. 22, no. 21, p. 8226, 2022.

[8] M. K. Pham, T. L. A. Nhan, N. T. T. Vuong, M. B. T. Nguyen, P. N. Nguyen, S. Sandiramourty, and T. T. H. Nguyen, “Empowering Vulnerable Populations through Technology: Innovations and Challenges in Social Work,” *Journal of Research in Educational Sciences*, vol. 15, no. 1, pp. 5-16, 2024.