

BRIDGING THE GAP BETWEEN RESEARCH AND PRACTICE: A SYSTEMATIC LITERATURE REVIEW OF IOT AND MACHINE LEARNING APPLICATIONS IN MENTAL HEALTHCARE SYSTEMS

Asokan Vasudevan¹, Rajendra N. Solanki^{*2}, Marcus Teunissen³, Wu Wenya⁴

1. Faculty of Business and Communications, INTI International University, Persiaran Perdana BBN Putra Nilai, 71800 Nilai, Negeri Sembilan, Malaysia
2. Department of Radiodiagnosis, Nootan Medical College & Research Centre, Sankalchand Patel University (SPU), Visnagar, Gujarat, India
3. Rushford Business School, Switzerland
4. Xingtai Vocational College of Applied Technology, Malaysia

*Correspondence: solankirn18@gmail.com

ABSTRACT

OBJECTIVE

This study conducts a systematic review of Internet of Things (IoT) and Machine Learning (ML) applications to identify existing gaps and scope for improvisation.

DESIGN

Databases such as Scopus, Web of Science, PubMed, IEEE Xplore, and ScienceDirect were searched to find relevant studies focusing on IoT and ML in mental healthcare. Using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, 18 studies were selected for the final review. Cyber-Physical Systems (CPS) theory and thematic analysis were employed to answer research questions.

RESULT/OUTCOMES

Four dimensions were identified as: continuous behavioural monitoring, ML-driven predictive analytics, real-time adaptive mental healthcare interventions, and responsible clinical deployment. IoT and ML technologies were found to have significantly improved patients' monitoring, predicting risks, and enhancing interventions using digital phenotyping, wearable data sensing, digital phenotyping and AI-driven analytics. However, some challenges in effective implementation of IoT and ML applications included explainability, ethical governance, interoperability, and clinical integration.

CONCLUSION

An Operational Framework for Real-Time IoT-ML Mental Healthcare Systems is proposed to bring together sensing, analytics, and interventions. This framework recommends taking adequate actions to support either scalability or clinically sustainable mental healthcare delivery.

KEYWORDS

Internet of Things; Machine Learning; Mental Healthcare System; Artificial Intelligence; Real-Time Implementation; Operational Framework

INTRODUCTION

Given the rise of mental health conditions, such as chronic stress, depression, anxiety, and behavioural dysfunction, the existing scenario of episodic consultations cannot be considered efficacious in the long run [1]. Mental health conditions have notably affected the quality of life and overall well-being of people across diverse populations. On top of that, current gaps in traditional psychiatric evaluations leave several people undiagnosed, leaving them either without any monitoring or with minimal interventions. Internet of Things (IoT), smartphones, wearable devices, and other advanced technologies have appeared in recent scholarly discussions in their potential to gather behavioural and physiological signals related to mental health. These signals often relate to speech and sleep patterns, Heart Rate Variability (HRV), and social interactions.

For example, a hybrid Machine Learning (ML) model can effectively interpret voice, facial expressions, and speech patterns, identifying the level of stress [2]. In sync with this, Del-Valle-Soto et al. [3] asserted a possibility of real-time feedback, gamification, and personalised interventions by integrating digital platforms with mental health. Growing research on digital phenotyping, one of the most effective processes to quantify individual-level human traits, confirms the predictive capabilities of wearable devices and smartphones in predicting the symptoms of insomnia, stress, depression, and other similar aspects [4, 5].

In spite of these developments, existing research is largely focused on technological aspects, which, to an extent, ignore the analytical and implementation-oriented synthesis of IoT and ML applications in mental healthcare delivery. The contribution of this research lies in integrating not only technological aspects, but also ethical dimensions and clinical implementation to address the gap between research and practice. To fulfil this objective, this study proposes an Operational Framework for Real-Time IoT-ML Mental Healthcare Systems to demonstrate phase-wise implementation of IoT and ML models.

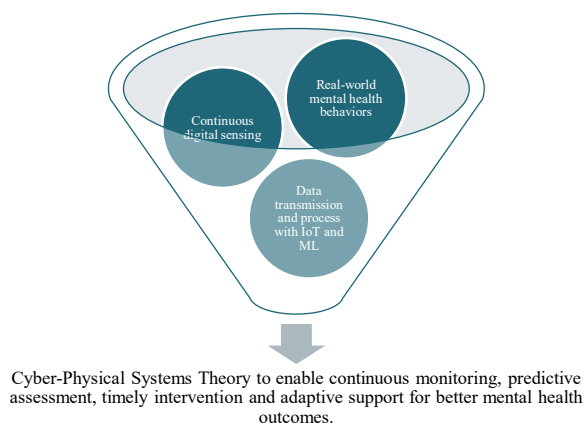
RQ1: What are the major applications of IoT and ML in mental healthcare systems?

RQ2: How can IoT and ML technologies guide intervention-oriented mental healthcare delivery, and what are the challenges in their practical implementation?

THEORETICAL FRAMEWORK

Cyber-Physical Systems (CPS) theory provides the foundation for this research. This theory discusses the integration of computational systems, intelligent analytics, and sensor technologies, and how this integration is useful for creating interdependent real-time systems [6]. This theory aims to merge physical (sensors, human environments, mechanical parts) with cyber (internet, computation) through constant feedback loops (Figure 1). This unifying factor of this theory closely aligns with this research study, which also focuses on improving real-time mental healthcare delivery by a combination of digital information and behavioural and computational aspects.

FIGURE 1. CPS THEORY



Source: Constructed by Authors

Bridging the Gap Between Research and Practice: A Systematic Literature Review of IoT and Machine Learning Applications in Mental Healthcare Systems

2

EVOLUTION OF MENTAL HEALTHCARE SYSTEMS

As per the World Health Organization (WHO) [7] report, approximately 970 million people suffered from mental health issues in 2019. Research by Queensland Brain Institute [8] suggests that more than 50% of people across the globe are likely to experience anxiety or depression at some point in their lives. Such statistics are concerning because depression and anxiety affect all realms of an individual's life, be it personal, professional, social, emotional, and more. Because of these all-encompassing adverse effects of mental health problems, early detection, real-time monitoring, and effective intervention have become a necessity to manage the stigma surrounding psychological issues and promote the overall life quality of people [9].

DIGITAL PHENOTYPING AND IOT IN MENTAL HEALTHCARE

While IoT devices such as smartphones, biosensors, and wearable sensors allow personalised care and real-time monitoring, cost-effective digital phenotyping can collect a wealth of data on digital phenotypes [10]. These are two significant aspects of transformation in mental healthcare systems because research has revealed significant potential in continuous anxiety and stress assessment using wearable devices [11]. Still, some authors, including Onnela and Rauch [12], have emphasised patients' consent in capturing their data. Similar issues, such as privacy, autonomy, confidentiality, need to be considered because of ethical issues in real-time surveillance.

ML AND PREDICTIVE MENTAL HEALTH ANALYTICS

With the continuously gathered data from the sensing devices based on Internet of Medical Things (IoMT), ML algorithms can be used to detect psychological patterns in people with depression, anxiety, stress, disorders, emotional stability and suicidal tendencies [13]. Specifically, Random Forest (RF) algorithms, Decision Trees, and Support Vector Machines (SVM) have demonstrated high potential in structuring behavioural datasets, and classifying and predicting risks.

Affirming this, Khoo et al. [14] have directly stated that these models can effectively classify depression, stress, and anxiety according to their severity levels, depending on sleep and voice patterns, along with social interactions and mobility of patients. Contrasting this, a study by Tuan [15] highlighted difficulties faced by clinicians in interpreting the results given by black-box Deep Learning (DL) models, causing trust issues. Additionally, many of these predictive models are based on biased or unbalanced datasets, which significantly affects the generalisability of findings and creates algorithmic bias. Overall, these challenges surrounding predictive models highlight notable gaps in these models' transition to intervention-oriented and clinically reliable systems.

INTERVENTION-ORIENTED SMART MENTAL HEALTHCARE SYSTEMS

Another key area is real-time intervention systems that can trigger emergency alerts to manage emotional crises, ongoing stress, and suicides [16]. In a study conducted by Zhang et al. [17], a real-time alert detection system achieved detection consistency of more than 95% across 12000 concurrent devices. This example reinforces the possibility of similar developments in mental healthcare delivery. These advanced developments should integrate psychosocial monitoring, behavioural analytics, and contextual awareness to improve personalised care. However, these intervention-oriented systems are still in pilot or experimental stages and have not so far shown sufficient clinical deployment. Furthermore, reliance on automated alerts raises concerns surrounding false alarms, limited human engagement, and ethical decision-making [18], [19], highlighting substantial gaps between technological innovation and practical implementation.

Overall, though existing research has demonstrated a fast evolution of advanced technologies, issues like lack of interpretability, limited accountability, and algorithmic bias remain large [18]. These challenges directly question ethical governance, emotional surveillance, explainability, and clinical validation of IoT-ML technologies, which can affect their implementation in healthcare on a large scale and on a sustainable basis.

RESEARCH GAPS

Key gaps across the reviewed studies include:

- Fragmented research surrounding ML prediction, IoT sensing, and digital phenotyping
- A limited number of studies with longitudinal data
- Less focus on intervention-orientation
- Limited studies focusing on clinical validation

METHODS

REVIEW PROTOCOL

The systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 [20] guidelines to ensure transparency and rigour in identifying, screening, and synthesising studies. Inclusion and exclusion criteria were predefined, and the quality of studies was assessed based on the Critical Appraisal Skills Programme (CASP).

SEARCH STRATEGY

A comprehensive search was conducted across academic databases, including Web of Science, Scopus, ScienceDirect, and PubMed, to shortlist relevant articles (based on inclusion/exclusion criteria, Table 1) between 2016 and 2026.

An extended search string was used across databases:

((("mental health*" OR anxi* OR depress* OR stress* OR "behavio* disorder*" OR psychiatr*) AND ("deep learning" OR "machine learning" OR "artificial intelligence" OR AI OR SVM OR CNN OR LSTM OR "random forest*") AND ("Internet of Things" OR IoT OR IoMT OR wearable* OR smartphone* OR biosensor* OR "digital phenotyping") AND (monitor* OR predict* OR intervention* OR telepsychiatr*)) where * denotes variations in the specific term.

TABLE 1. INCLUSION AND EXCLUSION CRITERIA

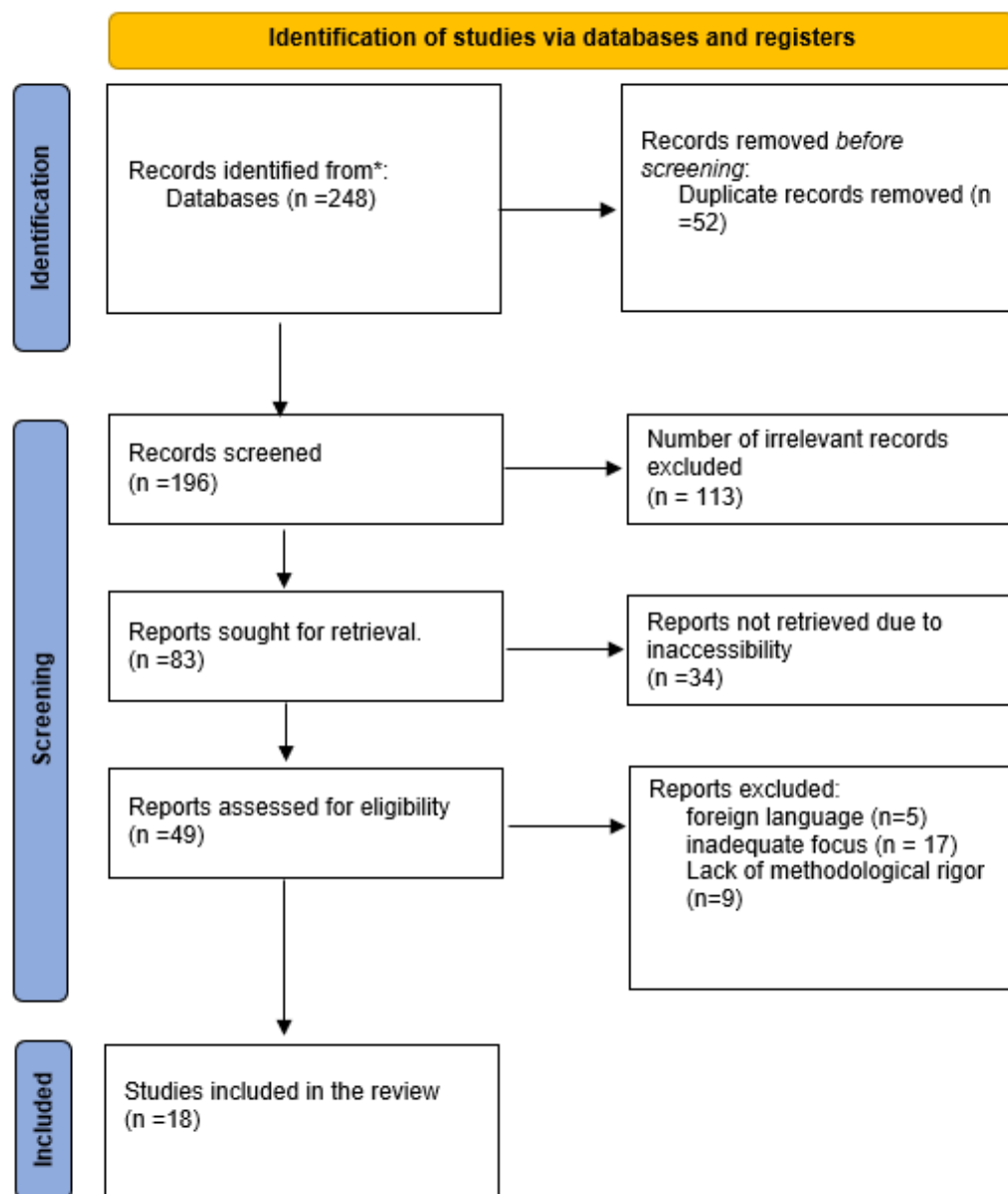
Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal articles	Editorials, opinion papers, and conference abstracts
Studies published in English	Non-English publications
Studies published between 2016 and 2026	Studies published before 2016
Empirical studies involving IoT and ML/DL in mental healthcare systems	Studies unrelated to mental healthcare applications and implementation
Studies reporting implementation outcomes, predictive performance, clinical validation, interoperability, scalability, or patient monitoring evidence	Conceptual papers without empirical validation
Pilot, longitudinal, experimental, observational, and real-world deployment studies relevant to mental healthcare	Duplicate studies, incomplete reports, and studies lacking sufficient methodological information

Source: Compiled by Authors

STUDY SELECTION PROCESS

Initially, 248 records were identified from different databases using the Boolean search string. After removing 52 duplicate records, the remaining 196 abstracts were screened. 113 studies were excluded as they did not meet the inclusion criteria; out of the remaining 83 records, 34 could not be retrieved. 49 records were assessed for eligibility based on their titles and abstracts; 31 were excluded after assessing the full text, and the remaining 18 were considered for the final review process (Figure 2).

FIGURE 2. PRISMA CHART



Source: Constructed by authors

CASP FRAMEWORK

The CASP assessment tool was used to evaluate studies on 7 dimensions (2 scores for each and a maximum score of 14) as listed below:

- Clear objectives
- Appropriate methodology
- Valid datasets
- Analytical rigour
- Evidence-based
- Ethical concerns
- Reproducibility

Studies between 12–14 were classified as high quality, 8–11 as moderate quality, and 0–7 as low quality (Table 2).

TABLE 2. SUMMARISATION OF LITERATURE

Author(s)	Technology / Model	Mental Healthcare Application	Key Findings	Relevance to the Present Study	Theme	Code	CASP Score
[1]	Mental health intervention review	Mental health challenges and interventions	Highlighted the increasing global burden of mental health disorders and limitations of existing intervention systems	Establishes the need for intelligent and scalable mental healthcare systems	Need for continuous and intervention-oriented healthcare	M3	11 (Moderate)
[2]	Wearable devices + physiological analytics	Real-time stress prediction	Demonstrated effectiveness of physiological signals for stress monitoring using wearable devices	Supports IoT-enabled continuous behavioural monitoring	IoT-based monitoring systems	M1	13 (High)
[3]	Wearable biometric systems	Behavioural and physiological monitoring	Explored wearable technologies for biometric sensing and behavioural assessment	Provides evidence for IoT sensing infrastructure in mental healthcare	IoT-based monitoring systems	M1	12 (High)
[4]	Passive sensing + ML	Mental health monitoring	Showed that wearable and smartphone sensing can support continuous behavioural	Supports digital phenotyping and continuous monitoring systems	IoT-based monitoring systems	M1	13 (High)

			monitoring and prediction				
[5]	Digital phenotyping	Stress, anxiety, and depression detection	Identified smartphone behavioural indicators associated with psychological disorders	Supports behavioural analytics and passive sensing approaches	IoT-based monitoring systems	M1	12 (High)
[6]	Cyber-Physical Systems (CPS) Theory	Intelligent integrated systems	Defined CPS as the integration of sensing, computational systems, and real-time analytics	Form the theoretical foundation of the present study	Intelligent healthcare ecosystems	M3	9 (Moderate)
[7]	Global healthcare evidence	Mental health prevalence	Highlighted the growing global burden of mental health disorders	Justifies the need for scalable mental healthcare solutions	Need for continuous and scalable healthcare	M3	10 (Moderate)
[8]	Epidemiological evidence	Mental health prevalence	Reported that nearly half the global population may experience mental disorders	Establishes urgency for preventive and continuous mental healthcare systems	Need for continuous and scalable healthcare	M3	10 (Moderate)
[9]	Mental health prevention strategies	Mental health promotion and prevention	Emphasised the need for early intervention and preventive healthcare approaches	Supports intervention-oriented mental healthcare systems	Intervention-oriented mental healthcare	M3	11 (Moderate)

[10]	IoT and digital healthcare technologies	Monitoring and intervention systems	Demonstrated IoT-based innovations for mental health monitoring and support	Supports operational and intervention-oriented healthcare frameworks	Intervention-oriented mental healthcare	M3	12 (High)
[11]	Wearable AI systems	Anxiety detection	Meta-analysis showed wearable AI systems can effectively detect anxiety through physiological data.	Supports ML-driven predictive analytics	ML-driven predictive analytics	M2	13 (High)
[12]	Smartphone digital phenotyping	Behavioural mental health analytics	Established smartphone sensing as a tool for continuous behavioural monitoring	Foundational evidence for digital phenotyping	IoT-based monitoring systems	M1	12 (High)
[13]	Passive sensing + ML	Continuous mental health monitoring	Highlighted predictive capabilities of smartphone and wearable sensing systems	Supports Theme 1 and Theme 2 development	ML-driven predictive analytics	M2	13 (High)
[14]	Multimodal ML models	Mental health detection	Demonstrated multimodal sensing improves prediction robustness	Supports ML-based behavioural intelligence systems	ML-driven predictive analytics	M2	12 (High)

			and accuracy				
[15]	Explainable AI (XAI)	Clinical AI implementation	Highlighted trust and transparency challenges of black-box AI systems	Supports ethical and explainability challenges	Ethical and implementation challenges	M4	11 (Moderate)
[16]	AI-driven mental healthcare systems	Addiction and complex mental health management	Demonstrated role of AI in adaptive and personalised mental healthcare interventions	Supports the intervention-oriented healthcare theme	Intervention-oriented mental healthcare	M3	11 (Moderate)
[17]	Predictive analytics + AI	Suicide risk and emotional distress prediction	Demonstrated predictive AI systems for crisis detection and prevention	Supports real-time intervention and crisis management systems	Intervention-oriented mental healthcare	M3	12 (High)
[18]	Generalizable ML systems	Stress monitoring from wearables	Identified limitations in dataset generalizability and real-world implementation	Supports implementation and validation challenges	Ethical and implementation challenges	M4	11 (Moderate)

Source: Compiled by authors

ANALYSIS AND RESULTS

THEMATIC ANALYSIS

A three-stage thematic analysis, comprising open coding, category formation, and theme generation, was employed to ensure analytical and methodical rigour and transparency of the research process (Table 3 and Table 4).

TABLE 3. THREE-STAGE CODING

Stage	Process Conducted	Example from Reviewed Studies	Output Generated
Stage 1: Open Coding	Key concepts, technologies, applications, and challenges were extracted from each study based on repeated ideas and research focus areas. Initial labels (codes) were assigned to recurring concepts.	Studies discussing wearable devices, passive sensing, smartphone monitoring, and physiological tracking were coded as “monitoring”, “behaviour tracking”, and “wearable sensing”. Studies focusing on Random Forest, CNN, and stress prediction were coded as “prediction models” and “AI analytics”.	Initial recurring codes related to monitoring, prediction, intervention, and implementation issues were identified.
Stage 2: Category Formation (Axial Coding)	Similar codes were grouped together based on conceptual similarity and operational function within mental healthcare systems.	Codes such as wearable sensing, behavioural tracking, passive sensing, and physiological monitoring were grouped under “IoT-based monitoring”. Codes related to depression prediction, anxiety detection, and multimodal AI models were grouped under “predictive analytics”.	Broader analytical categories representing core research areas were developed.
Stage 3: Final Theme Development (Selective Coding)	The broader categories were synthesised into higher-level themes that represent the major dimensions of IoT- and ML-enabled mental healthcare systems.	Monitoring-related categories formed Theme M1, prediction-related categories formed Theme M2, intervention-focused categories formed Theme M3, and governance/privacy-related categories formed Theme M4.	Four final analytical themes were generated: M1 (Monitoring Systems), M2 (Predictive Analytics), M3 (Real-Time Adaptive Mental Healthcare Interventions), and M4 (Responsible and Clinically Sustainable Mental Healthcare Deployment).

Source: Compiled by authors

TABLE 4. CODES

Code	Theme
M1	IoT-Based Monitoring Systems
M2	ML-Based Predictive Analytics
M3	Real-Time Adaptive Mental Healthcare Interventions
M4	Responsible and Clinically Sustainable Mental Healthcare Deployment

Source: Compiled by authors

The frequency analysis of studies demonstrated in Table 5 reveals the concentration of literature surrounding four broad dimensions, i.e., M1, M2, M3, and M4. M3, the most predominant dimension appearing in more than 40% of the studies, relates to real-time adaptive mental healthcare interventions, which reflects the growing research orientation in real-time, intervention-based models. IoT-based monitoring systems (M1), appearing in approximately 27 % of the studies, highlighted that wearable sensing, digital phenotyping, and passive behavioural tracking are frequent approaches when

it comes to mental health assessment. In contrast, relatively fewer (approximately 16 %) studies talked about ML-driven predictive analytics, and only 2 studies out of 18 discussed ethical and implementation challenges.

This analysis directly shows that while innovation in technologies is growing, ethical concerns remain a concern requiring comprehensive attention. The analysis also reinforces the need for more analytically integrated and implementation-oriented mental healthcare frameworks that combine continuous monitoring, predictive intelligence, ethical governance, and actionable intervention mechanisms.

TABLE 5. FREQUENCY ANALYSIS

Code	Theme	Number of Studies	Percentage (%)	Interpretation
M1	IoT-Based Monitoring Systems	5	27.8%	Literature strongly focuses on wearable sensing, passive monitoring, and behavioural data collection for mental health assessment.
M2	ML-Driven Predictive Analytics	3	16.7%	Several studies emphasise predictive modelling, multimodal analytics, and AI-based mental health detection systems.
M3	Real-Time Adaptive Mental Healthcare Interventions	8	44.4%	The majority of studies highlight the growing need for scalable, preventive, and intervention-oriented mental healthcare ecosystems.
M4	Responsible and Clinically Sustainable Mental Healthcare Deployment	2	11.1%	Compared with other studies, fewer critically address explainability, privacy, validation, and implementation barriers.

Source: Compiled by Authors

THEME 1: REAL-TIME ADAPTIVE MENTAL HEALTHCARE INTERVENTIONS (M3) (RQ2)

Real-time adaptive interventions have been shown to improve continuity of care, accessibility of health services, risk management, and personalised mental healthcare delivery [10], [16], [18]. From the CPS theory's perspective, intervention systems combine computation and sensing as IoT devices monitor behavioural and physiological conditions, and ML models detect psychological risks. Thus, CPS-based ecosystems ensure smooth and continuous workflows not only in a predictable way but also in an action-oriented manner. However, these intervention systems are still in an experimental stage, and their large-scale clinical use is not yet established.

THEME 2: CONTINUOUS BEHAVIOURAL MONITORING SYSTEMS (M1) (RQ1, RQ2)

IoT-enabling monitoring systems are the foundation of smart mental healthcare solutions because continuous sensing is beneficial in detecting mental health risks over periodic assessments [2], [4], [5]. These systems, being CPS-based interconnected infrastructures, generate continuous digital data and ensure computational analysis by making that data measurable. Thus, monitoring systems ensure continual mental healthcare by effective physiological and behavioural monitoring, signifying a promising application of IoT.

THEME 3: ML-DRIVEN PREDICTIVE MENTAL HEALTH ANALYTICS (M2) (RQ1, RQ2)

Various algorithms, including SVM, RF, CNN, and LSTM, are frequently used for the classification of depression, prediction of stress, classification of emotions, and suicide risk prediction. According to the studies by Abd-Alrazaq et al. [11] and

Khoo et al. [14], the advantages of multimodal ML systems are that they leverage on behavioural, physiological, and contextual data to achieve predictive robustness. CPS theory underpins this theme with a focus on the dynamic interplay between sensing and computational decision-making subsystems, in which the continuously generated behavioural data are translated into predictive healthcare intelligence. However, the literature also reveals tensions regarding explainability, algorithmic bias, and limited clinical validation, indicating that predictive performance currently advances faster than practical implementation reliability.

THEME 4: RESPONSIBLE AND CLINICALLY SUSTAINABLE MENTAL HEALTHCARE DEPLOYMENT (M4)

Adverse impacts are observed on clinician trust with the use of Black-Box AI and emotional surveillance; consent issues and sensitive data security are raised with continued IoT-based behavioural monitoring. The findings of other studies, including those by Tuan [15] and by Vos et al. [19], also reveal a lack of diversity in datasets and a lack of adequate longitudinal validation that limits the confidence in implementing those studies in the real world. In the CPS paradigm, there is a need for secure, transparent and reliable interaction among the sensing infrastructures, computational systems and healthcare environments to build a sustainable mental healthcare ecosystem. To ensure effective implementation, predictive capability must also be combined with explainable AI architectures, interoperable healthcare systems, trusted data governance, and clinically rigorous decision-support tools. The results indicate that the rate of technological innovation in the realms of IoT and ML is outpacing that of ethical and clinical deployment, resulting in a significant disparity between the development of the technology and its practical application in healthcare.

Collectively, existing literature has significantly advanced across M1, M2, M3, and M4 themes; however, it predominantly focuses on isolated technological functions rather than explaining how sensing, analytics, intervention, and governance interact within mental healthcare systems. From a CPS perspective, this gap limits the full realisation of operational mental healthcare systems, indicating a need for a proposed action-oriented conceptual framework. Operational Framework for Real-Time IoT-ML Mental Healthcare Systems integrates continuous monitoring, predictive intelligence, adaptive intervention mechanisms, and responsible clinical implementation into a unified intelligent mental healthcare architecture.

PROPOSED CONCEPTUAL FRAMEWORK

After analysing, based on the CPS theory, the framework outlines the continuous sensing through IoT devices, the conversion into computational intelligence using ML analytics, the generation of adaptive healthcare actions and the anchoring through responsible clinical implementation mechanisms. The framework, therefore, demonstrates the real-time interaction between sensing infrastructures, predictive analytics, intervention systems, and governance structures within intelligent mental healthcare ecosystems. The framework is intentionally structured into four operational phases to ensure implementation clarity. As indicated in Table 6, Phase 1 involves persistent behavioural acquisition from the use of wearable devices, mobile phones, biosensors and tele-sensing. In Phase 2, AI- and ML-powered analytics engines that are able to detect stress, depression, anxiety, emotional instability and suicide-risk patterns are placed in operation, enabling predictive mental state detection. Phase 3 translates predictive outputs into adaptive healthcare interventions such as telepsychiatry consultations, AI-based Cognitive Behavioural Therapy (CBT) systems, behavioural recommendations, and emergency escalation workflows. Phase 4 ensures responsible clinical integration through explainable AI, cybersecurity protocols, interoperability standards, clinician oversight, governance systems, and long-term clinical validation.

To improve practical applicability, the framework further identifies specific implementation tools, technologies, operational steps, and responsible entities required at each phase, as shown in Table 7. This provides healthcare organisations with a transparent implementation roadmap rather than a purely descriptive conceptual model. The framework, therefore, bridges the gap between technological innovation and real-world mental healthcare deployment by demonstrating how IoT and ML systems can be operationalised into scalable, adaptive, and clinically sustainable mental healthcare ecosystems.

TABLE 6. OPERATIONAL FRAMEWORK FOR REAL-TIME IOT-ML MENTAL HEALTHCARE SYSTEMS

Phase	Operational Layer	What It Does	Key Technologies / Processes	Real-Time Healthcare Outcome
Phase 1	Continuous Behavioural Acquisition	Continuously captures physiological, behavioural, and contextual mental health indicators.	Wearables, smartphones, biosensors, IoMT devices, passive sensing	Real-time behavioural visibility and patient monitoring
Phase 2	Predictive Mental State Detection	Identifies abnormal psychological patterns and mental health risks through computational analysis	ML/DL models (SVM, RF, CNN, LSTM), multimodal analytics	Early-risk detection for stress, anxiety, depression, and suicide risk
Phase 3	Adaptive Healthcare Intervention	Converts predictive outputs into immediate and personalised mental healthcare actions	Telepsychiatry systems, AI-based CBT, crisis alerts, behavioural recommendation systems	Real-time intervention and adaptive healthcare delivery
Phase 4	Responsible Clinical Integration	Ensures secure, explainable, interoperable, and clinically sustainable implementation	Explainable AI (XAI), governance systems, interoperability frameworks	Trustworthy and scalable mental healthcare deployment

Source: Compiled by Authors

TABLE 7. TOOLS, TECHNOLOGIES, OPERATIONAL STEPS, AND RESPONSIBLE ENTITIES REQUIRED AT EACH PHASE

Phase	Tools / Steps / Approaches for Implementation	Responsible Entity for Implementation
Phase 1	Deploy wearable devices (Fitbit, Apple Watch, EEG bands), integrate smartphone sensing apps, establish cloud-based behavioural data collection infrastructure, implement digital phenotyping protocols, and integrate APIs with EHR systems.	Mental health clinics, hospital IT departments, IoMT vendors, mobile health application developers, wearable technology providers, and clinical informatics teams
Phase 2	Train ML models on behavioural datasets, integrate predictive AI engines into healthcare platforms, establish AI-supported clinical dashboards, implement NLP-based emotional analysis, and automate clinician risk scoring systems	Data scientists, AI engineers, clinical data analysts, hospital AI research teams, healthcare analytics companies, and psychiatrists validating predictive outputs
Phase 3	Deploy AI-powered CBT chatbots, integrate telepsychiatry platforms, establish suicide-risk escalation workflows, implement automated alert systems, integrate clinician notification protocols, and enable mobile-based patient engagement systems	Psychiatrists, psychologists, telepsychiatry teams, crisis response units, behavioural therapists, hospital operations teams, mental health support staff
Phase 4	Implement explainable AI dashboards, establish clinician-in-loop review systems, deploy cybersecurity and encrypted storage protocols, adopt interoperability standards (FHIR, HL7), conduct clinical validation studies, and establish AI governance and bias-monitoring frameworks	Healthcare regulators, hospital governance boards, ethics committees, cybersecurity teams, compliance officers, AI governance bodies, healthcare policymakers, clinical auditors

Source: Compiled by Authors

DISCUSSION AND LIMITATIONS

IoT and ML technologies are changing mental healthcare from the periodical psychiatric evaluation model to a more continuous, predictive, and intervention-oriented approach to healthcare delivery. Although much literature highlights wearable sensing and predictive analytics, on the other hand, less work has been directed to the aspects of real-life implementation, accessibility, explainability and the deployment of such tools in a clinically sustainable approach.

One potential limitation of this study is that few studies are included (n=18), which could limit the generalisability and richness of the themes emerging across a wide range of mental health care settings. A number of reviewed studies have examined this in pilot/experimental settings, but were limited in longer-term clinical implementation, scalability and patient outcome assessment. Further, some of these studies are highly focused on the predictive value and the feasibility of technology, offering limited discussion of interoperability, clinician feasibility, cost feasibility, and organisation readiness to deploy. The proposed operational model is conceptually synthesised from existing literature, and as such, needs to be validated with empirical analysis in real-world healthcare systems offering mental health services. Future researchers can extend this study by empirically validating the proposed operational framework through pilot implementation within real-world mental healthcare settings to evaluate clinical effectiveness, scalability, interoperability, and patient outcomes.

CONCLUSIONS

This study illustrates how continuous monitoring, predictive behaviour analytics, adaptive interventions and scalable mental healthcare delivery can be achieved by embedding IoT and ML technologies within CPS-supported healthcare ecosystems. Operational Framework for Real-Time IoT-ML Mental Healthcare Systems unifies the architectures of sensing, analytics, intervention, and responsible deployment.

References

1. Magomedova A, Fatima G. Mental health and well-being in the modern era: A Comprehensive Review of Challenges and Interventions. *Cureus* 2025; 17(1). <https://doi.org/10.7759/cureus.77683>
2. Lazarou E, Exarchos TP. Predicting Stress Levels Using Physiological Data: Real-Time Stress Prediction Models Utilising Wearable Devices. *AIMS Neurosci* 2024; 11(2):76. <https://doi.org/10.3934/Neuroscience.2024006>
3. Del-Valle-Soto C, Briseño RA, Valdivia LJ, Nolasco-Flores JA. Unveiling Wearables: Exploring the Global Landscape of Biometric Applications and Vital Signs and Behavioral Impact. *BioData Min* 2024; 17(1):15. <https://doi.org/10.1186/s13040-024-00368-y>
4. Shen et al. Passive Sensing for Mental Health Monitoring Using Machine Learning with Wearables and Smartphones: Scoping Review. *J Med Internet Res* 2025; 27:e77066. <https://doi.org/10.2196/77066>
5. Choi A, Ooi A, Lottridge D. Digital Phenotyping for Stress, Anxiety, and Mild Depression: Systematic Literature Review. *JMIR Mhealth Uhealth* 2024; 12(1):e40689. <https://doi.org/10.2196/40689>
6. Baheti R, Gill H. Cyber-Physical Systems. *Cyber-physical Systems*. In: Samad T, Annaswamy AM, editors. *The Impact of Control Technology*. Piscataway (NJ): IEEE Control Systems Society; 2011. 161-6. <https://ieeecs.org/sites/ieeecs/files/2019-07/loCT-Part3-02CyberphysicalSystems.pdf>
7. WHO. Mental Health. WHO. 2025. Available: https://www.who.int/health-topics/mental-health#tab=tab_2 (Accessed 16/05/26)
8. Harvard Medical School. Half of World's Population Will Experience a Mental Health Disorder. [Internet]. 2023. Available: <https://hms.harvard.edu/news/half-worlds-population-will-experience-mental-health-disorder> (Accessed 16/05/26)
9. Singh V, Kumar A, Gupta S. Mental Health Prevention And Promotion—A Narrative Review. *Front Psychiatry* 2022; 13:898009. <https://doi.org/10.3389/fpsy.2022.898009>
10. Al Khatib I, Ndiaye M, Shamayleh A. Advancing Mental Healthcare Through IoT and Digital Technologies: Innovations in Monitoring, Intervention, And Support. *Bull Natl Res Cent* 2026; 50(1):40. <https://doi.org/10.1186/s42269-026-01419-6>
11. Abd-Alrazaq A et al. Wearable artificial intelligence for detecting Anxiety: Systematic Review and Meta-Analysis. *J Med Internet Res* 2023; 25:e48754. <https://doi.org/10.2196/48754>
12. Onnela JP, Rauch SL. Harnessing smartphone-based digital phenotyping to Enhance Behavioral and Mental Health. *Neuropsychopharmacology* 2016; 41(7):1691-6. <https://doi.org/10.1038/npp.2016.7>
13. Bin Heyat MB et al. Intelligent internet of medical things for depression: Current Advancements, Challenges, and Trends. *Int J Intell Syst* 2025; 2025(1):6801530. <https://doi.org/10.1155/int/6801530>
14. Khoo LS, Lim MK, Chong CY, McNaney R. Machine learning for Multimodal Mental Health Detection: A Systematic Review of Passive Sensing Approaches. *Sensors*. 2024; 24(2):348. <https://doi.org/10.3390/s24020348>
15. Tuan DA. Bridging the Gap Between Black Box AI And Clinical Practice: Advancing Explainable AI for Trust, Ethics, and Personalized Healthcare Diagnostics [Preprint]. 2024; 2. <https://doi.org/10.20944/preprints202409.1974.v2>
16. Ajayi R. AI-powered Innovations for Managing Complex Mental Health Conditions and Addiction Treatments. *Int Res J Modern Eng Technol Sci* 2025; 7(1):87. Available: https://www.researchgate.net/profile/Rhoda-Ajayi-2/publication/387730444_AI-POWERED_INNOVATIONS_FOR_MANAGING_COMPLEX_MENTAL_HEALTH_CONDITIONS_AND_ADDICTION_TREATMENT_S/links/6779f80f894c552085430abe/AI-POWERED-INNOVATIONS-FOR-MANAGING-COMPLEX-MENTAL-HEALTH-CONDITIONS-AND-ADDICTION-TREATMENTS.pdf
17. Zhang H, Zhang R, Sun J. Developing Real-Time IoT-based Public Safety Alert and Emergency Response Systems. *Sci Rep* 2025; 15(1):29056. <https://doi.org/10.1038/s41598-025-13465-7>

18. Adepoju AG et al. AI in Crisis Prediction and Prevention: Leveraging Predictive Analytics for Suicide Risk and Emotional Distress Management. *Int J Biol Pharm Sci Arch* 2025; 10(2):049-064. <https://doi.org/10.53771/ijbpsa.2025.10.2.0078>
19. Vos G, Trinh K, Samyati Z, Azghadi MR. Generalizable Machine Learning for Stress Monitoring from Wearable Devices: A Systematic Literature Review. *Int J Med Inform* 2023; 173:105026. <https://doi.org/10.1016/j.ijmedinf.2023.105026>
20. Page MJ et al. The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. *BMJ*. 2021; 372. <https://doi.org/10.1136/bmj.n71>