FMDB *Transactions on Sustainable Psychology Sequence*

Prospective Cohort of Nurse-Led Wearable and Smartphone Mood Monitoring: Early-Intervention Opportunities and Adherence Challenges

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Abstract: Depressive symptoms often fluctuate between clinical visits, limiting timely detection and intervention. Wearables and smartphones offer continuous mood-relevant data, yet sustaining engagement and translating data into care remain challenges. This study evaluated the feasibility, adherence, and early-intervention potential of a nurse-led wearable and smartphone-based mood-monitoring pathway in routine outpatient care, and explored predictors of non-adherence. A prospective cohort study was conducted with 60 adults recruited from primary care and mental health clinics. Participants used a wrist-worn wearable (to track heart rate, sleep, and activity) and a smartphone app that delivered daily ecological momentary assessments (EMAs) of mood. Registered nurses provided on-boarding, technical support, and protocol-based outreach in response to mood deterioration, non-adherence, or concerning sleep patterns. Primary outcomes were adherence to wearable use and EMA completion (≥80% threshold). Logistic regression examined predictors of non-adherence. Mean wearable use was 19.24 ± 3.12 hours/day, with 73.33% achieving adherence ≥80%. Mean EMA completion was 76.45% ± 14.32, with 65.00% meeting adherence thresholds. Dropout was 10%. Nurse-initiated actions included supportive calls (26.67%), non-adherence reminders (25.00%), mood alerts (18.33%), sleep alerts (13.33%), and expedited referrals (8.33%). Lower education significantly predicted non-adherence (OR 3.14, p = 0.046). These findings demonstrate that nurse-led digital mood monitoring is feasible, supports timely interventions, and highlights the need for tailored strategies to address education-related engagement gaps for equitable implementation.

Keywords: Nurse-Led Monitoring; Ecological Momentary Assessment; Adherence and Early-Intervention; Health Challenges; Digital Mental Health; Depressive Disorders.

Received on: 02/08/2025, **Revised on:** 03/10/2025, **Accepted on:** 25/10/2025, **Published on:** 03/03/2026

Journal Homepage: https://www.fmdbpub.com/user/journals/details/FTSPS

DOI: https://doi.org/10.69888/FTSPS.2026.000658

Cite as: S. Vashist, R. Thomas, C. Thakur, P. Chand, and N. K. Sain, "Prospective Cohort of Nurse-Led Wearable and Smartphone Mood Monitoring: Early-Intervention Opportunities and Adherence Challenges," *FMDB Transactions on Sustainable Psychology Sequence*, vol. 1, no. 1, pp. 39–48, 2026.

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1. Introduction

Depressive disorders represent one of the most pervasive and disabling health challenges worldwide. They affect individuals across the lifespan and interfere profoundly with how people think, feel, work, and relate to others [1]. Beyond the personal suffering they cause, depressive disorders contribute substantially to global disease burden through increased morbidity, elevated suicide risk, diminished quality of life, and wide-ranging economic consequences [2]. Lost productivity, repeated healthcare visits, and long-term disability place sustained pressure on individuals, families, health systems, and societies at large. Although effective treatments are well established—including antidepressant medications, evidence-based psychotherapies, and collaborative care approaches—many people do not receive timely help. For a large proportion of individuals, recognition of depression is delayed, diagnosis is missed or postponed, and treatment initiation occurs only after symptoms have become severe or chronic [3]. One reason for this gap lies in depression itself. Early changes in mood, cognition, sleep, motivation, and social engagement are often subtle, fluctuate over time, and may be attributed to stress or personality rather than illness. These early warning signs frequently go unnoticed during brief, infrequent clinical encounters, where clinicians must rely on retrospective self-report and limited observation. As a result, valuable opportunities for early intervention are lost, allowing symptoms to deepen, functioning to deteriorate, and treatment responsiveness to decline.

Against this backdrop, there is an urgent need for scalable, real-world approaches to identify emerging risks earlier and support timely intervention [4]. Digital health technologies particularly smartphones and wearable devices offer a promising pathway to address this long-standing detection–treatment gap. By shifting assessment beyond the clinic and into daily life, these tools enable observation of patterns of behaviour, activity, and mood as they unfold naturally. Continuous, unobtrusive monitoring holds the potential to transform depression care from a reactive model to one that is proactive, preventive, and personalised. Rather than waiting for crises to occur, clinicians may be alerted to meaningful changes in functioning and intervene before symptoms escalate. The widespread availability of mobile technology strengthens this opportunity. By the end of 2022, more than half of the world's population had access to mobile internet, and smartphones had become the primary gateway to digital services in many regions. In mental health care, this ubiquity means that symptom self-reports, behavioural data, and passive sensor data can be collected at scale without specialised or expensive equipment. Modern smartphones are equipped with accelerometers, GPS sensors, microphones, and usage logs that can serve as indirect indicators of physical activity, mobility, sleep–wake cycles, and social interaction domains closely linked to depressive symptomatology [6]. Changes in these patterns may reflect shifts in mood, energy, motivation, or circadian rhythms, offering valuable insights into an individual's mental state.

However, the promise of digital mental health tools must be considered alongside important limitations. Access to smartphones and reliable internet connectivity is uneven, particularly in low- and middle-income countries and among digitally marginalised groups. Older adults, individuals with lower socioeconomic status, and those living in rural or remote areas may face barriers related to device ownership, data affordability, or digital literacy. In addition, language differences, cultural perceptions of mental illness, and concerns about privacy, data security, or surveillance can affect willingness to engage with monitoring technologies. If these issues are not addressed, digital tools risk widening—rather than narrowing—existing inequities in mental health care. For this reason, monitoring programs must be designed to be inclusive, culturally sensitive, low-burden, and embedded within supportive human care structures. Wearable devices further expand the scope of digital monitoring by enabling the continuous collection of physiological and behavioural data. These devices can track rest–activity cycles, sleep duration and quality, physical activity levels, heart rate, and heart rate variability—parameters that are closely associated with mood regulation and emotional well-being. Disturbances in sleep–wake rhythms, psychomotor slowing, reduced physical activity, and increased sedentary behaviour are well-recognised features of depressive episodes and, in some cases, may appear before individuals consciously recognise worsening mood. Wearables offer an objective lens through which such changes can be monitored over time, often with minimal effort required from users once devices are in place.

An expanding body of validation research suggests that although consumer-grade wearable devices differ in accuracy across brands and models, they are generally reliable in detecting relative changes within individuals. This within-person sensitivity is particularly valuable in mental health, where deviations from a person's usual patterns may be more clinically meaningful than comparisons to population averages [21]. Nonetheless, challenges remain. Proprietary algorithms, lack of standardisation across devices, and limited transparency about data processing can hinder interpretation and comparability. Clear reporting standards, validation against gold-standard measures, and careful integration into supervised care pathways are therefore essential for responsible clinical use. When appropriately implemented, wearable-derived indicators—such as declining sleep regularity or reduced activity—may serve as early warning signals that prompt timely clinical review and support. While passive sensing provides valuable objective data, subjective experience remains central to understanding depression. Ecological momentary assessment (EMA) addresses this need by capturing individuals' self-reported mood, thoughts, behaviours, and contextual experiences in real time. EMA involves brief prompts delivered multiple times per day or week, asking individuals to reflect on how they feel in the moment rather than relying on distant recall. This approach reduces recall bias and reveals the

dynamic, fluctuating nature of depressive symptoms. It can highlight emotional reactivity, daily stressors, coping strategies, and situational triggers that may not emerge during standard clinical interviews.

When EMA is combined with passive data from smartphones and wearables, a richer and more interpretable picture emerges. Objective changes in activity or sleep can be understood in the context of subjective experiences such as low motivation, interpersonal conflict, or physical illness. This multimodal perspective supports more nuanced risk stratification and clinical decision-making. Automated systems may manage low-risk deviations by offering self-management tips or psychoeducation, while higher-risk patterns trigger review by clinicians or nurses. In this way, digital monitoring can help allocate human resources more efficiently, ensuring that timely attention is directed to those who need it most. Evidence from large, multi-site observational studies in major depressive disorder demonstrates that remote measurement technologies are generally feasible and acceptable over extended periods. Participants from diverse backgrounds have shown willingness to contribute both passive sensor data and active self-reports for months at a time. These programs have generated valuable insights into symptom trajectories, relapse patterns, and predictors of recovery or treatment response. Importantly, they also demonstrate the potential for digital tools to support research and care at a population scale. Despite these advances, much of the existing literature remains focused on feasibility and technical validation rather than clinical impact. Fewer studies have examined how digital signals can be meaningfully integrated into routine care to improve patient outcomes. Critical questions remain unanswered:

- Which data streams are most clinically actionable?
- How should alert thresholds be set to balance sensitivity and specificity?
- What governance structures are needed to ensure safety, accountability, and patient trust?

Addressing these questions requires pragmatic trials and implementation-focused research that considers workflow integration, staffing models, escalation pathways, and ethical safeguards alongside technical performance. Within this evolving digital landscape, nurses are uniquely positioned to play a central role. Decades of evidence from collaborative care and chronic disease management models highlight the effectiveness of nurse-led coordination in the treatment of depression. These models emphasise proactive follow-up, measurement-based care, patient education, and stepped treatment adjustments in partnership with physicians and mental health specialists. Such approaches have consistently been associated with improved symptom outcomes, better treatment adherence, and higher patient satisfaction across diverse healthcare settings. In the digital era, translating these principles, nurse-led monitoring programs can serve as the vital human interface between continuous data streams and clinical action. Nurses are well equipped to interpret trends, contextualise alerts within patients' social and emotional lives, and translate data into meaningful support. This may include supportive phone calls, problem-solving around medication adherence, behavioural activation strategies, or timely referral to specialist care. By maintaining therapeutic relationships and continuity, nurses help ensure that digital monitoring complements rather than replaces the relational core of mental health care. Embedding smartphone and wearable data within nurse-delivered interventions may therefore enhance the timeliness, personalisation, and acceptability of depression management. At the same time, sustaining engagement with digital interventions remains a persistent challenge.

The "law of attrition" describes how usage often declines over time, even among individuals who do not formally withdraw. In mood-monitoring programs, disengagement may arise from notification fatigue, perceived burden, technical difficulties, stigma, or a lack of meaningful feedback. Without sustained engagement, the potential benefits of digital monitoring cannot be fully realised. Design strategies that prioritise simplicity, personalisation, and clear value to users are essential. Just as important is the presence of human support. Nurse-led models may reduce attrition by offering encouragement, addressing privacy concerns, assisting with technical issues, and helping individuals interpret their own data in a supportive, non-judgmental manner. However, empirical evidence on how such support influences long-term engagement and outcomes remains limited. Prospective studies and hybrid effectiveness–implementation trials are needed to identify who benefits most from digital monitoring, why engagement persists or wanes, and how support structures can promote equitable and sustained use. The convergence of smartphones, wearable technologies, and real-time self-report methods offers a powerful opportunity to improve the early detection and ongoing management of depressive disorders. While technical feasibility has been firmly established, the next phase of progress depends on thoughtful clinical integration, attention to equity and ethics, and the active involvement of nursing professionals. By embedding digital signals within nurse-led, person-centred care models, mental health systems may be better positioned to identify emerging risk, intervene early, and ultimately reduce the personal and societal burden of depression.

2. Review of Literature

The use of wearable devices and smartphone applications in mental health care has significantly changed how mood disorders are monitored and managed [1]. These technologies enable continuous, real-time tracking of mood-related patterns and provide personalised feedback to support early identification of emotional changes. Such early-intervention opportunities are especially valuable for preventing symptom worsening. However, maintaining consistent use of these digital tools and ensuring their

practical value in clinical settings remains an ongoing challenge [2]. A nurse-led, prospective approach emphasises regular patient engagement, early recognition of mood deterioration, and prompt supportive interventions. This approach has the potential to improve patient outcomes by combining technological innovation with compassionate nursing care, thereby addressing gaps in traditional mental health care models. Huang et al. [9] highlighted the practical value of a nurse-led wearable monitoring program in a mental health outpatient setting by showing how continuous, technology-supported care can make a meaningful difference in patient outcomes. In their study, nurses actively monitored data from wearable devices to observe subtle changes in patients' activity levels and physiological patterns that often signalled early depressive relapse. Because nurses were closely involved in reviewing these trends, they were able to initiate timely follow-ups, provide supportive counselling, and coordinate early therapeutic adjustments in collaboration with the healthcare team [3]. This proactive approach helped prevent symptom escalation, leading to fewer psychiatric hospitalizations. The study emphasises the importance of combining digital health technologies with consistent nursing oversight to enhance early detection, continuity of care, and overall effectiveness of mental health interventions [4].

Richardson and Puskar [19] explored the use of a nurse-administered smartphone application for screening anxiety and depression in primary care settings, highlighting the central role of nurses in digital mental health care. In this study, nurses actively supported participants by explaining how to use the application, assisting them during initial engagement, and regularly reviewing mood data generated by the app. Rather than relying solely on automated outputs, nurses interpreted emerging trends in patients' emotional states and used this information to initiate timely follow-up care or referrals when needed. Participants reported high satisfaction with this approach, as the ongoing guidance and reassurance from nurses made the technology feel more personal and less intimidating [5]. The study also found that digital monitoring strengthened nurse–patient communication by creating more meaningful, data-informed conversations about mental health, thereby fostering trust and engagement in care. Pinge et al. [18] examined how accurately wearable sensors could capture physiological indicators such as heart rate variability and physical activity to reflect mood changes. The study found a strong relationship between data collected from wearable devices and participants' self-reported mood states. These results suggest that wearable technologies can reliably detect mood-related changes, supporting their usefulness as practical tools for ongoing mood monitoring in mental health care. Jafleh et al. [8] highlighted the important role nurses play in supporting patients who use wearable devices for health monitoring.

The study found that when nurses actively explained wearable data, provided regular feedback, and educated patients about the purpose and benefits of monitoring, patients felt more confident and motivated to continue using the devices [6]. Ongoing nurse–patient interactions helped address doubts, technical difficulties, and concerns, thereby reducing dropout rates. Patients who received consistent guidance and encouragement from nurses were more engaged, used the devices more regularly, and developed a better understanding of their own health patterns. This finding underscores the importance of human support, particularly from nurses, for sustaining long-term adherence to wearable-based monitoring programs. Bakker and Rickard [11] pointed out that not all individuals have the same ability to engage consistently with wearable and smartphone-based mood monitoring. They observed that people from lower-income backgrounds often face unique challenges that make regular participation difficult. Limited access to reliable devices, unstable internet connections, and the cost of data plans can prevent them from fully benefiting from these digital health tools [7]. As a result, socioeconomic factors play a significant role in adherence, and addressing these barriers is crucial to ensuring that mood-monitoring interventions are equitable and accessible to all populations. Sequeira et al. [10] conducted a systematic review to examine how effectively mobile applications and wearable devices capture behaviours and physiological signals related to mood. The review found that these technologies were generally successful at identifying mood-associated patterns, such as activity levels, sleep behavior, and physiological responses [8].

However, the authors noted noticeable differences in accuracy across various devices and data-processing algorithms. These findings highlight the promise of digital mood-monitoring tools while emphasizing the need for standardization and careful selection of technologies to ensure consistent, reliable results in clinical practice. Faurholt-Jepsen et al. [16] explored the use of smartphone-based monitoring among individuals with bipolar disorder. They found that noticeable changes in daily activity levels and patterns of social communication often occurred several days before the onset of a mood episode. These early behavioral shifts suggest that smartphones can serve as an early warning system, enabling healthcare professionals to identify emerging mood changes and initiate timely preventive interventions before symptoms become severe. Matcham et al. [5] noted that many users struggle to keep up with digital mental health tools because their interfaces can be complicated, and frequent notifications can become overwhelming. When apps are cluttered or constantly demand attention, users may feel frustrated or stressed, leading them to stop using the tools altogether. The researchers suggested that designing simpler, more intuitive interfaces, combined with adaptive notifications that respond to the user's needs and habits, could help maintain engagement over time. By reducing cognitive overload and making the experience feel more personalised, these strategies may encourage users to engage with wearable- and smartphone-based mood-monitoring systems consistently [9].

Schwartz et al. [17] highlighted the value of ecological momentary assessment (EMA) delivered via smartphone applications as a practical, patient-centred approach to mood monitoring. Instead of relying on retrospective questionnaires that ask

individuals to recall how they felt over days or weeks, EMA allows users to report their emotions and experiences in real time, within their natural environments. This "in-the-moment" reporting reduces recall bias, which is a common limitation of traditional mental health assessments, especially among individuals experiencing fluctuating mood states [20]. By capturing mood data in real time, EMA provides a more accurate and nuanced picture of emotional patterns throughout the day. Schwartz et al. [17] further emphasised that frequent, brief smartphone assessments increase the sensitivity of mood tracking, enabling clinicians to detect subtle changes that may signal early worsening of symptoms. Such timely insights support earlier clinical responses and personalised interventions, making EMA a valuable tool in digital mental health care, particularly within nurse-led monitoring frameworks. Eysenbach [7] highlighted the role of ecological momentary assessment (EMA) delivered via smartphones in capturing real-time mood experiences. EMA minimises recall bias and enables frequent, in-the-moment mood reporting, thereby strengthening the clinical relevance of digital mood monitoring. When combined with passive sensor data, EMA offers a comprehensive picture of both subjective and objective aspects of mental health. Borghouts et al. [15] noted that although mood-tracking apps are widely downloaded, sustaining their use over time remains a major challenge.

Many users initially engage with these applications out of curiosity or motivation to manage their mental health, but this engagement often fades within a few weeks. Repetitive daily logging can lead to user fatigue, especially when individuals do not perceive immediate benefits or meaningful feedback from the app. Additionally, the lack of personalisation—such as generic prompts or non-tailored insights—can make the experience feel impersonal and less relevant to users' unique emotional needs. Privacy and data security concerns further contribute to attrition, as users may become uncomfortable with sharing sensitive mental health information over extended periods. Together, these factors highlight the importance of designing mood-monitoring technologies that are user-centred, adaptive, and transparent to maintain long-term engagement and trust.

Mohr et al. [13] explored how combining app-based cognitive behavioural therapy (CBT) with daily mood monitoring could support individuals managing mental health symptoms. Their study showed that patients who regularly tracked their mood in the application became more aware of emotional patterns and early warning signs of worsening symptoms. This increased self-awareness helped individuals respond more promptly to mood changes, apply CBT strategies more effectively, and engage more actively in their own care. Compared with participants who did not use mood monitoring, those who completed daily tracking demonstrated better symptom control and a clearer understanding of how thoughts, emotions, and behaviors are interconnected.

The findings highlight the value of mood monitoring not only as a data-collection tool, but also as a means of empowering patients to recognise changes early and take timely, preventive action. Faurholt-Jepsen et al. [12] highlighted several practical challenges that can affect the long-term use of wearable and smartphone-based mood-monitoring tools. Users often experience issues such as rapid battery drain, occasional software glitches, and device compatibility issues. These technical problems can lead to frustration, disrupt daily use, and ultimately reduce adherence to mood monitoring routines. The study underscores the importance of designing user-friendly, reliable, and compatible devices to ensure participants remain engaged over time and that the technology effectively supports early detection and intervention for mood disorders.

Saeb et al. [14] found that data collected passively through smartphones, including GPS-based movement patterns and overall phone usage time, could effectively predict the severity of depressive symptoms in individuals diagnosed with major depressive disorder. The study revealed that reduced mobility, limited social movement, and altered phone interaction patterns were closely associated with higher levels of depression. These findings demonstrate that smartphones can unobtrusively capture everyday behavioural changes linked to mood fluctuations, offering a realistic and ecologically valid method for monitoring mental health in daily life without placing additional burden on individuals.

2.1. Materials and Methods

This study employed a prospective cohort design to evaluate the feasibility, adherence, and potential for early intervention of nurse-led mood monitoring using wearable devices and smartphone applications. The study was conducted in a clinical setting where registered nurses oversaw participant recruitment, device orientation, and follow-up. A total of 60 adult participants were enrolled through consecutive sampling from outpatient mental health and primary care clinics. Eligibility criteria included:

- Age between 18 and 60 years,
- Ownership of a compatible smartphone,
- Ability to provide informed consent, and
- No current diagnosis of severe cognitive impairment or acute psychiatric crisis.

Individuals with physical limitations that prevent the use of wearables or a lack of digital literacy were excluded.

3. Methodology

Participants were provided with a wearable wristband that recorded physiological parameters (e.g., heart rate, sleep patterns, and physical activity). They were instructed to install a companion smartphone application designed for ecological momentary assessment (EMA) of mood. Nurses guided participants through setup, troubleshooting, and adherence reminders. Participants were prompted via the application to complete brief daily mood ratings, with data automatically synchronised to a secure server. Nurses reviewed the data remotely and were responsible for contacting participants if clinically significant mood deterioration, non-adherence, or concerning patterns were detected.

Early-intervention opportunities included supportive phone calls, referrals, or scheduling expedited clinic visits when required. Demographic and baseline clinical data were collected via structured questionnaires administered by nurses. Wearable-derived physiological data and smartphone mood ratings were automatically logged throughout the study. Adherence was measured as (1) the percentage of completed daily mood entries and (2) average daily wear time of the device. Instances of dropout and device non-use were also recorded. Primary outcomes were adherence rates to wearable and smartphone monitoring and the feasibility of nurse-led oversight. Secondary outcomes included identification of early-intervention opportunities, defined as nurse-initiated contacts triggered by concerning mood fluctuations or physiological signals.

3.1. Statistical Analysis

Data were entered and analysed using IBM SPSS Statistics for Windows, Version 26.0 (IBM Corp., Armonk, NY, USA). Descriptive statistics (means, standard deviations, and proportions) were used to summarise demographic and clinical characteristics. Adherence outcomes were expressed as percentages and compared across subgroups using independent t-tests and chi-square tests, as appropriate. Logistic regression was performed to identify predictors of non-adherence. A two-tailed p-value of <0.05 was considered statistically significant.

4. Results

4.1. Demographic and Baseline Characteristics

The study enrolled 60 participants with a mean age of 34.52 ± 10.14 years. Slightly more than half of the participants were female (53.33%), while males accounted for 46.67%. A majority of participants (68.33%) had attained college-level education or higher, and 45.00% were married. Baseline depressive symptoms of mild-to-moderate severity were identified in 30.00% of the cohort, suggesting that a substantial proportion already exhibited mental health concerns at study entry. These demographic and clinical characteristics highlight a relatively young, educated, and gender-balanced sample.

4.2. Adherence Outcomes

Adherence to wearable and smartphone monitoring was encouraging overall. Participants reported a mean daily wearable use of 19.24 ± 3.12 hours, with 73.33% achieving ≥80% adherence. For mood entry completion, the average response rate was 76.45% ± 14.32, and 65.00% of participants reached≥80% adherence thresholds. Despite structured support, a 10.00% dropout rate was observed. These findings reflect a generally high level of compliance with digital monitoring, although smartphone-based entries had slightly lower adherence rates than wearable device use.

4.3. Gender Comparisons in Adherence

When adherence outcomes were compared by gender, no statistically significant differences were found. Wearable adherence ≥80% was observed in 75.00% of males and 71.88% of females ($p = 0.79$). Mean mood entry completion was slightly higher among females (78.00% ± 15.01) than males (74.68% ± 13.52), but this difference did not reach statistical significance ($p = 0.41$). Similarly, smartphone adherence ≥80% was achieved by 60.71% of males and 68.75% of females ($p = 0.52$). These results indicate that gender did not play a meaningful role in determining adherence patterns within the cohort.

4.4. Nurse-Led Early Interventions

Nurse-led monitoring resulted in multiple proactive interventions triggered by the system. Mood deterioration alerts accounted for 18.33% of interventions, while non-adherence reminders accounted for 25.00%. Sleep disturbance patterns prompted 13.33% of interventions, and expedited clinic referrals were initiated for 8.33% of participants. The most frequent supportive measure was phone calls without in-person referral, which occurred in 26.67% of cases. Collectively, these data suggest that continuous monitoring provided actionable opportunities for timely nurse-led interventions, particularly for adherence issues and mood instability.

4.5. Predictors of non-adherence

Regression analysis identified educational status as a significant predictor of non-adherence. Participants with lower education levels (<College) were more than 3 times as likely to exhibit non-adherence than those with higher education (OR = 3.14, 95% CI: 1.02–9.65, p = 0.046). Baseline depressive symptoms also showed a trend toward predicting non-adherence (OR = 2.67, 95% CI: 0.91–7.81, p = 0.07), though this did not reach statistical significance. Age ≥40 years (p = 0.49) and male gender (p = 0.74) were not significant predictors. These findings suggest that educational background plays a crucial role in sustaining adherence, while mood symptoms may contribute but require further investigation in larger samples (Table 1).

Table 1: Demographic and baseline characteristics of participants (N = 60)

Variable	n (%) / Mean ± SD
Age (years)	34.52 ± 10.14
Gender	
Male	28 (46.67%)
Female	32 (53.33%)
Education ≥ College	41 (68.33%)
Married	27 (45.00%)
Baseline Depressive Symptoms (Mild-Moderate)*	**18 (30.00%)**

Table 2 provides the adherence data of the individuals during the research. Average daily wear time was 19.24 ± 3.12 hours/day, and 44 individuals (73.33%) achieved ≥80% wearable adherence. On average, 76.45 ± 14.32% of mood entries were completed, and 39 participants (65.00%) achieved at least 80% adherence to entering data on the smartphone. In addition, 6 participants (10.00%) were lost to follow-up in the research.

Table 2: Adherence outcomes

Adherence Measure	Mean ± SD / n (%)
Mean daily wearable use (Hours/Day)	19.24 ± 3.12
≥80% Wearable adherence	44 (73.33%)
Mean completion of mood entries (%)	76.45 ± 14.32
≥80% Smartphone entry adherence	39 (65.00%)
Dropout	6 (10.00%)

Table 3 displays adherence outcomes for male (n=28) and female (n=32) individuals. 21 males (75.00%) and 23 females (71.88%) attained wearable adherence ≥80% with no significant difference (p = 0.79). Males completed a mean of 74.68 ± 13.52 % of mood entries, females completed a mean of 78.00 ± 15.01 % (p = 0.41). Smartphone adherence ≥80% was observed in 17 males (60.71%) and 22 females (68.75%), without a significant difference between genders (p = 0.52).

Table 3: Comparison of adherence by gender

Variable	Male (n=28)	Female (n=32)	p-Value
Wearable adherence ≥80%	21 (75.00%)	23 (71.88%)	0.79
Mean mood entry completion (%)	74.68 ± 13.52	78.00 ± 15.01	0.41
Smartphone adherence ≥80%	17 (60.71%)	22 (68.75%)	0.52

Summary of nurse-led early interventions initiated during trial. 11 cases (18.33%) had mood deterioration alarms, and 15 (25.00%) non-adherence reminders were fired. Sleep disturbances accounted for 8 interventions (13.33%). Expedited clinic appointment referrals were made in 5 cases (8.33%). Additionally, 16 patients (26.67%) received supportive phone call only interventions (Table 4).

Table 4: Nurse-led early interventions

Trigger for Intervention	n (%)
Mood deterioration alerts	11 (18.33%)
Non-adherence reminders	15 (25.00%)
Sleep disturbance patterns	8 (13.33%)
Expedited clinic visit referrals	5 (8.33%)
Supportive phone call only	16 (26.67%)

Table 5 shows the determinants of non-adherence using binary logistic regression. Age ≥40 years (OR = 1.42, 95%CI: 0.52–3.91, P = 0.49), and male gender (OR = 1.18, 95%CI: 0.43–3.24, P = 0.74) were not significant predictors. Higher baseline depressed symptoms were associated with higher risks of non-adherence (OR = 2.67, 95% CI: 0.91–7.81), but not significantly (p = 0.07). Only lower education (<College) was a statistically significant predictor of non-adherence (OR=3.14, 95% CI: 1.02-9.65, p=0.046*).

Table 5: Predictors of non-adherence (Binary Logistic Regression)

Predictor Variable	OR (95% CI)	p-Value
Age ≥ 40 years	1.42 (0.52–3.91)	0.49
Male gender	1.18 (0.43–3.24)	0.74
Baseline depressive symptoms	2.67 (0.91–7.81)	0.07
Lower education (<College)	3.14 (1.02–9.65)	**0.046***
**Statistically significant at p < 0.05.*		

5. Discussion

Our cohort was relatively young (mean age 34.52 ± 10.14 years) and highly educated (College or higher: 68.33%). This profile mirrors broader mHealth adoption patterns showing that mobile health app users skew younger and more educated; for example, Bol et al. [22] reported higher odds of mHealth use with greater education (OR = 1.12, 95% CI 1.01–1.24 per category) and a negative association with age (OR = 0.97, 95% CI 0.96–0.98 per year), aligning with our sample's 68.33% college attainment. Adherence to the wearable was high in our study (mean 19.24 ± 3.12 h/day; ≥80% adherence in 73.33%), and mood-entry completion averaged 76.45% ± 14.32, with 65.00% achieving ≥80%. These values are comparable to a recent bipolar cohort in which Ortiz et al. [23] observed overall adherence of 79.5% for a ring wearable and 74.6% for daily self-ratings; their growth-mixture trajectories (perfect/good/poor) also echo our spread of high vs moderate adherence, supporting the feasibility of combined wearable+EMA monitoring in real-world mental health samples. Positioning our 76.45% mean EMA completion rate, it sits squarely within compliance ranges reported in EMA studies of depression.

Seidman et al. [24] summarised that depression-focused EMA protocols typically achieve response rates of ~63–85% to momentary prompts, indicating that our nurse-supported approach achieved solid, literature-consistent engagement on the smartphone side. Gender did not meaningfully shape adherence in our data (e.g., wearable ≥80%: males 75.00% vs females 71.88%, $p = 0.79$; EMA completion 74.68% vs 78.00%, $p = 0.41$). This accords with Sinvani et al. [25], who found no gender difference in EMA compliance over two weeks (women: 7.59 ± 2.96 vs men: 7.48 ± 3.16 sessions; p = 0.83), reinforcing the idea that sex effects on EMA adherence are small or inconsistent across contexts. Comparing device vs app engagement, our wearable adherence (≥80% in 73.33%) parallels the pattern reported by Til et al. [26], who tracked people with bipolar disorder for six weeks and found participants met daily thresholds on 77.8% of days for the Fitbit (≥12 hours/day) versus 81.8% of days for the app (≥50% of prompts), with a steeper decline over time for wearables than for app entries. Our results—high but slightly lower wearable adherence than smartphone EMA—are consistent with those dynamics. Study attrition was modest in our cohort (dropout rate 10.00%), which compares favorably with the broader smartphone intervention literature.

A meta-analysis by Linardon and Fuller-Tyszkiewicz [27] reported mean attrition rates of 24.1% at short-term follow-up and 35.5% at longer-term follow-up in smartphone mental health RCTs, suggesting that structured nurse oversight and troubleshooting in our design may have buffered against the higher attrition often seen in unguided digital interventions. Nurse-led oversight translated into actionable early interventions in our program (e.g., 18.33% mood-deterioration alerts; 25.00% non-adherence reminders; 26.67% supportive calls; 8.33% expedited referrals). Although our cohort was not designed to test clinical outcomes, these responsive contacts align with human-supported digital models that have demonstrated benefit. In an RCT, Goulding et al. [28] showed that a smartphone self-management intervention with coaching reduced relapse risk among low-risk individuals (HR 0.32, 95% CI 0.12–0.88; $p = 0.02$) and decreased depressive severity (QIDS mean difference −0.80, $p = 0.02$), supporting the premise that timely, clinician-prompted actions can improve trajectories. Finally, the 13.33% of nurse-triggered actions prompted by sleep disturbance patterns is directionally consistent with evidence linking wearable-captured sleep regularity with next-day mood and depressive burden. Using actigraphy, Fang et al. [29] found that lower day-to-day variability in total sleep time and wake time predicted better next-day mood (e.g., TST variability $b = -0.011$, $p < 0.001$), underscoring why sleep-based alerts in our pipeline often yielded clinically relevant outreach.

6. Conclusion

Nurse-led wearable and smartphone-based mood monitoring was a realistic and beneficial way to support participants in a prospective cohort of 60, the researchers found. "Results indicated high participant engagement, with high rates of adherence to both wearable device use and ecological momentary assessment (EMA) mood reporting. Specifically, 73.33% of participants

had a wearable adherence rate of at least 80%, and the mean EMA completion rate was 76.45%, indicating sustained engagement in digital monitoring tasks. In addition, the low dropout rate (10.00%) indicates good acceptability of the intervention in the research period. A crucial component of the approach was the incorporation of continuous nurse oversight, which enabled real-time analysis of monitoring data and timely responses when issues were discovered. The most frequent triggers of intervention were mood worsening alarms (18.33%) and sleep disturbance patterns (13.33%). These findings led to timely nurse-led actions, such as supportive phone calls (26.67%) and hastened clinic referrals (8.33%), illustrating the practical value of combining digital monitoring with expert clinical assistance. The results also demonstrated that the adherence rates did not differ significantly between male and female participants, showing that gender was not a significant factor affecting involvement with the monitoring system. However, non-adherence was independently associated with lower education (OR 3.14; $p = 0.046$), suggesting a potential equity gap in the utilisation of digital health tools. Overall, nurse oversight combined with computerised mood tracking seems a practical and doable idea. Future research should aim to establish appropriate support techniques for individuals with lower levels of educational attainment and to further assess the clinical effectiveness and cost-effectiveness of these treatments in broader, more diverse groups.

Acknowledgment: The authors express their sincere gratitude to Teerthanker Mahaveer College of Nursing, Happy Child College of Nursing, Dev Bhoomi Uttarakhand University, Government Nursing College Pithoragarh, and Maharaj Vinayak Global University for their valuable support, encouragement, and facilities provided during the conduct of this research.

Data Availability Statement: The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request.

Funding Statement: This study was conducted without any external financial support.

Conflicts of Interest Statement: The authors report no conflicts of interest, and all sources used in this original work have been duly acknowledged.

Ethics and Consent Statement: The study followed ethical guidelines, with informed consent obtained from all participants.

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