



Mobile Health Technologies for Real-Time Neuroendocrine Monitoring of Mental Health Disorders in Underserved African Populations

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ABSTRACT

Mental health disorders impose a severe burden across Sub-Saharan Africa, yet the treatment gap exceeds 90% in most countries. A central reason for this gap is the absence of objective, real-time physiological monitoring tools at the community level, compounded by a mobile technology access gap that still leaves women 26% less likely than men to use mobile internet in the region [1]. Mobile health (mHealth) technologies such as wearable biosensors, point-of-care cortisol assays, and cloud-based clinical decision tools provide a technically feasible pathway for monitoring the neuroendocrine correlates of depression, anxiety, and post-traumatic stress disorder (PTSD) outside hospital settings. This paper presents a narrative review, conducted in line with the PRISMA 2020 reporting guideline of peer-reviewed literature published between 2012 and 2026 [2]. It synthesizes evidence on the neuroendocrine physiology of common mental health disorders, the monitoring capacity of current mHealth devices, the implementation context of underserved communities in Sub-Saharan Africa, and the regulatory environment governing digital mental health data. The review demonstrates that heart rate variability (HRV), electrodermal activity (EDA), and salivary cortisol are valid and accessible neuroendocrine markers for mental health monitoring and that mHealth platforms can deliver these measurements through community health workers without specialist psychiatric personnel. The paper proposes the mHealth Neuroendocrine Mental Health Monitoring Framework (mNEMF) and provides six evidence-based policy recommendations for scaling this innovation within African health systems.

Keywords: Mhealth; Neuroendocrine Monitoring; Mental Health; Cortisol; Heart Rate Variability; Sub-Saharan Africa

INTRODUCTION

Mental health disorders such as depression, anxiety disorders, and PTSD represent a major and rising source of disability across Sub-Saharan Africa. The World Health Organization estimates that 116 million people in the region live with a diagnosable mental health condition, yet fewer than one in ten receives any treatment [3]. This treatment gap has four identifiable causes: a shortage of trained psychiatric professionals, community stigma, the absence of community-based diagnostic infrastructure, and the complete lack of objective physiological monitoring tools at the primary

care level [4-5]. A fifth, compounding factor is that non-communicable diseases, injuries, and mental health conditions together now form a "triple burden" projected to cause more premature deaths on the continent than any other cause category by 2030, a convergence that has driven the African Union and Africa Centres for Disease Control and Prevention (Africa CDC) to adopt a dedicated multisectoral mental health strategy [6].

The fourth cause is the least studied and the most amenable to technological innovation. Mental health diagnosis and follow-up in Sub-Saharan Africa currently

depends on clinical interview and symptom rating scales. These instruments require trained personnel, capture only a single moment of mental state, and produce no continuous biological data [7]. This is a significant limitation because depression, anxiety, and PTSD each produce measurable, real-time perturbations in the neuroendocrine system specifically the hypothalamic-pituitary-adrenal (HPA) axis and the autonomic nervous system that hold diagnostic value independent of self-report [8-9]. The chronic activation and dysregulation of these systems under prolonged psychosocial adversity is captured by the concept of allostatic load, the cumulative physiological wear that repeated or poorly terminated stress responses impose on the body [10].

Wearable biosensors can now measure HRV and EDA continuously, and emerging wearable artificial intelligence models classify depressive states from these continuous signals with pooled diagnostic accuracies exceeding 80% across validation studies [11]. Lateral flow immunoassay strips enable point-of-care measurement of salivary cortisol with a smartphone camera [12]. These tools, combined with cloud-based clinical decision platforms and the broader concept of digital phenotyping, the moment-by-moment quantification of an individual's physiological and behavioural state from personal digital devices have the potential to extend objective neuroendocrine mental health monitoring into communities where the treatment gap is most severe [13]. Realising this potential, however, depends on closing the mobile technology access gap: Sub-Saharan African women remain 26% less likely than men to use mobile internet, and affordability of internet-enabled handsets remains the dominant barrier to adoption in the region [1,14]. This paper examines the evidence for that potential and proposes a framework for its implementation.

Scholarly Contribution

This paper makes three original contributions as follows

- It is the first synthesis to link the specific neuroendocrine physiology of mental health disorders to the monitoring capacity of current mHealth devices in the Sub-Saharan African context.
- It provides quantitative evidence that HRV, EDA, and salivary cortisol are sufficiently sensitive and specific for community-level mental health monitoring without specialist equipment.
- It proposes the mNEMF as an original operational model designed for the structural constraints of African primary health care, community health worker programmes, and the regulatory environment governing digital health data on the continent.

CONCEPTUAL AND LITERATURE REVIEW

Neuroendocrine Physiology of Mental Health Disorders

Three neuroendocrine mechanisms are disrupted across the most prevalent mental health disorders in Sub-Saharan African populations: HPA axis regulation, autonomic cardiovascular control, and sympathetic nervous system reactivity [8]. Glucocorticoids, the principal hormonal output of the HPA axis, exert permissive, suppressive, stimulatory, and preparative actions on the stress response; when their secretion becomes chronically dysregulated rather than self-limiting, the resulting allostatic load damages the very systems the stress response was meant to protect [10,15].

In major depressive disorder (MDD), cortisol secretion is sustained rather than episodic, producing elevated basal cortisol and a flattened diurnal cortisol slope. This pattern is present in approximately 50% of patients with MDD and predicts poor treatment response and recurrence. In anxiety disorders, the HPA axis shows heightened reactivity to stressors and impaired cortisol recovery, indicating failure of the negative feedback regulation that normally terminates the cortisol response. In PTSD, basal cortisol is suppressed while the sympathoadrenal system remains chronically overactivated; pooled prevalence estimates place probable PTSD at 22% across Sub-Saharan African populations generally and at 30% in conflict-exposed regions specifically [16].

Autonomic nervous system dysregulation, measured through HRV, accompanies all three disorders. HRV reflects the balance between sympathetic and parasympathetic influences on heart rhythm. Reduced HRV indicates reduced parasympathetic tone, impaired emotional regulation, and elevated cardiovascular risk [9]. EDA, measured as galvanic skin response, reflects sympathetic nervous system arousal and is significantly elevated in anxiety disorders and PTSD.

Neuroendocrine dysregulation in Sub-Saharan Africa is further compounded by two population-specific stressors. First, gender-based violence, which affects an estimated 45% of women across the region, elevates HPA axis and autonomic reactivity independently of any pre-existing diagnosis and is strongly associated with comorbid depression, anxiety, and PTSD among survivors [17]. Second, HIV infection interacts bidirectionally with mental health; pooled prevalence estimates place depression among people living with HIV in Sub-Saharan Africa between 9% and 36%, driven partly by direct neuroendocrine and immune effects of chronic infection and partly by the psychosocial burden of managing a stigmatised chronic illness [18]. Both stressors are common in the underserved communities that mHealth neuroendocrine monitoring is intended to reach.

mHealth Technologies for Neuroendocrine Monitoring

Wearable biosensors incorporate photoplethysmography (PPG) sensors for continuous HRV measurement, galvanic skin response sensors for EDA monitoring, accelerometers, and skin temperature sensors. Wrist-worn PPG-based HRV measurement shows a concordance correlation coefficient of 0.87 to 0.93 with gold-standard electrocardiographic measurement across published validation studies [19]. This level of accuracy is sufficient for community mental health monitoring without clinical-grade equipment. A scoping review of wearable EDA sensors similarly confirms their capacity to detect perceived stress across laboratory and field settings, although the review notes that most validation to date has occurred in high-income care contexts rather than community field conditions of the kind found in Sub-Saharan Africa [20].

Point-of-care cortisol assays using lateral flow immunoassay strips, readable by smartphone camera, achieve 89% sensitivity and 84% specificity for detection of elevated cortisol in field conditions [12]. Timed salivary sampling protocols such as morning cortisol and afternoon cortisol-to-DHEA ratio are feasible for community health worker administration and provide clinically meaningful HPA axis data for mental health triage decisions. Cloud-based clinical decision tools aggregate biosensor and cortisol data and produce interpreted risk scores accessible to community health workers without specialist training. A systematic review and meta-analysis of wearable artificial intelligence models for depression detection found pooled classification accuracies that support their use as a screening layer ahead of clinician review, although the review cautions that most underlying training data originate from high-income populations and require local recalibration before African deployment [11]. This recalibration need is consistent with the broader digital phenotyping literature, which emphasises that passively collected physiological and behavioural signals must be validated within the specific population and context in which they will be applied before being used for clinical decision-making [13].

Mental Health Burden in Underserved African Communities

The burden of mental health disorders in underserved Sub-Saharan African communities is substantial and is amplified by poverty, food insecurity, displacement, gender-based violence, and HIV comorbidity which independently dysregulate the HPA axis and autonomic nervous system [7]. The treatment gap in most countries exceeds 90%, driven by a shortage of psychiatrists and the near-total absence of community-based objective monitoring tools [3,21]. This burden does not occur in isolation; the African Union's Common Position on non-communicable diseases, injuries, and mental health explicitly recognises these three domains as a combined, mutually reinforcing threat to health system capacity across

the continent, and calls for multisectoral rather than siloed policy responses [6].

Three structural features of these communities make mHealth neuroendocrine monitoring relevant. First, they have minimal access to psychiatric services. Second, they have growing but unevenly distributed access to mobile phones in urban and peri-urban areas, with smartphone adoption in the region projected to rise from 51% to 88% by 2030 even as a persistent gender gap in mobile internet use continues to disadvantage women [1,14]. Third, they are served by established community health worker (CHW) programmes that provide a delivery channel for mHealth monitoring without new workforce development [5,22]. However, CHW density across the continent ranges from 11.2 to 59.5 workers per 10,000 population depending on working arrangements, meaning that any mHealth model must be designed for realistic, and highly variable, staffing levels rather than an idealised full-time CHW workforce [23].

Existing mHealth Mental Health Evidence in Africa

mHealth interventions for mental health in Sub-Saharan Africa have focused on delivering psychological content via smartphone platforms. The Friendship Bench programme in Zimbabwe and the StrongMinds platform in Uganda demonstrate that community health workers can deliver structured mental health interventions through mobile platforms with strong fidelity and community acceptance [24]. Trials in South Africa, Uganda, Kenya, and Nigeria report significant reductions in depression and anxiety symptom scores following these interventions [22]. Meta-analytic evidence from smartphone-delivered mental health interventions more broadly finds moderate reductions in depressive symptoms across randomized controlled trials supporting the plausibility of combining psychological content delivery with physiological monitoring on the same platform [25].

A broader review of digital health implementations for community and primary health workers across the continent similarly found that mHealth solutions achieve effective usage where onsite training, intuitive application design, and stakeholder involvement are prioritised, but that limited network connectivity, unreliable power supply, and low digital literacy remain recurring barriers [26]. Where telepsychiatry has been layered onto these platforms for remote specialist input, resource-constrained health systems in South Africa, Kenya, and Nigeria have reported feasible and clinically effective outcomes, although national scale-up has been slowed by inconsistent broadband infrastructure and a shortage of accredited remote-consultation protocols [27].

Economic evidence further supports this direction. A systematic review of integrating mental health services into primary care across low- and middle-income countries found that task-shared, technology-supported models were consistently more cost-effective than specialist-only care,

even though the review identified very few African-specific cost-effectiveness studies [28].

A critical gap in all these models is the absence of continuous objective physiological monitoring. Interventions capture symptom changes only through self-report rating scales at fixed intervals. Real-time neuroendocrine data like HRV, EDA, and cortisol are not collected, which means that physiological deterioration between assessment points goes undetected. The mNEMF proposed in Section 4.3 addresses this gap directly.

Regulatory and Data Governance Context

The scale-up of neuroendocrine mHealth monitoring cannot be separated from the regulatory environment that governs the resulting physiological data. At least 29 African countries now have documented data protection policies, and regional bodies including the African Union, ECOWAS, and the Southern African Development Community have established minimum data-processing standards [29]. However, an analysis of South Africa's Protection of Personal Information Act, National Health Act, and Consumer Protection Act found significant gaps in the regulation of AI-driven digital mental health tools specifically, including insufficient guidance on third-party data sharing and cross-border data transfer, despite South Africa having one of the continent's more developed data protection frameworks [29]. At the global level, the WHO Global Strategy on Digital Health 2020–2025 calls on member states to strengthen governance for digital health at national and international levels, including regulatory frameworks for evidence-based digital health solutions, but implementation of this guidance remains uneven across Sub-Saharan Africa [30]. Because continuous neuroendocrine data is more sensitive, and more re-identifiable, than episodic symptom scores, the mNEMF proposed in this paper treats data governance as a core design component rather than an afterthought.

METHODOLOGY

Study Design

This paper employs a narrative review design. This approach is appropriate for a multidisciplinary evidence base spanning neuroendocrine physiology, digital health technology, psychiatric epidemiology, and African health systems research. The review synthesizes evidence from peer-reviewed studies and policy reports published between 2012 and 2026.

Search Strategy and Inclusion Criteria

The following databases were searched: PubMed, Scopus, PsycINFO, African Journals Online (AJOL), and Google Scholar. Search terms included: "mHealth AND mental health Africa"; "heart rate variability AND depression Africa"; "cortisol AND anxiety Sub-Saharan Africa"; "wearable biosensor AND mental health

monitoring"; "HPA axis AND mHealth"; and "digital health governance AND Africa." Studies were included when they met the following criteria: the study reported neuroendocrine or validated clinical outcomes; the study was relevant to mental health conditions, mHealth monitoring technology, or the digital health regulatory environment; and the study was relevant to low-resource or Sub-Saharan African populations, published between 2012 and 2026. Study identification, screening, and reporting followed the structure of the PRISMA 2020 statement, adapted for a narrative rather than systematic synthesis [2].

Ethical Considerations

This study is based on published secondary literature only. No primary data collection was conducted and no institutional ethical approval was required. The review follows the PRISMA guidelines adapted for narrative synthesis [2].

RESULTS

Neuroendocrine Biomarkers Available for mHealth Monitoring

Three neuroendocrine biomarkers emerged from the review as both clinically valid markers of mental health status and technically accessible to current mHealth devices in low-resource settings: HRV, EDA, and salivary cortisol.

HRV is the most extensively validated marker. RMSSD values are significantly reduced in MDD, generalized anxiety disorder, and PTSD relative to healthy controls, with effect sizes sufficient to support clinical triage at the community level [9]. Wrist-based PPG measurement of RMSSD achieves concordance correlation coefficients of 0.87 to 0.93 with gold-standard ECG measurement, confirming its validity for field use without clinical-grade equipment [19]. EDA captured by galvanic skin response sensors provides a real-time measure of sympathetic nervous system arousal specific to anxiety and PTSD in naturalistic environments, and wearable EDA sensing has been shown feasible across both laboratory and field studies [20]. Salivary cortisol via lateral flow immunoassay, with smartphone camera reading, achieves 89% sensitivity and 84% specificity for elevated cortisol detection and can distinguish the hypercortisolaemia of depression and anxiety from the hypocortisolaemia of PTSD when diurnal sampling protocols are applied [12]. The physiological basis for combining these three markers rests on the well-established permissive and preparative actions of glucocorticoids on autonomic and behavioural systems, meaning that cortisol, HRV, and EDA signals are not independent but reflect converging outputs of the same underlying allostatic process [15].

mHealth Technology Evidence in African Mental Health Settings

Evidence from mHealth mental health studies conducted in Sub-Saharan Africa confirms three findings. First, smartphone access is sufficient to support mHealth mental health monitoring in urban and peri-urban areas across the region, although this access remains unevenly distributed by gender [1]. Second, community health workers can be trained to administer biosensor monitoring protocols to acceptable fidelity within two to five days of structured training a finding consistent with the wider evidence on digital health implementation for African community and primary health workers, which shows that onsite training and intuitive application design are the strongest predictors of successful adoption [22,26]. Third, patients in low-resource African settings show high acceptance of wearable monitoring devices when the purpose and benefit are explained clearly before use [24].

Five implementation barriers were identified consistently: intermittent internet connectivity in rural areas; device cost and durability in low-income settings; data privacy concerns in communities where mental health stigma is high, compounded by uneven enforcement of existing data protection laws limited capacity of community health workers to interpret raw physiological outputs without clinical decision support; and variable CHW staffing density across countries [23,29]. The mNEMF described below addresses each of these barriers directly.

The mHealth Neuroendocrine Mental Health Monitoring Framework (mNEMF)

The mNEMF is a six-component sequential model for deploying neuroendocrine mental health monitoring through community health worker programmes in Sub-Saharan Africa.

Component 1: Neuroendocrine Data Capture.

Community health workers administer wearable biosensors measuring HRV and EDA and guide patients through timed salivary cortisol collection using lateral flow immunoassay strips readable by a standard smartphone camera. Patients wear biosensor devices between scheduled CHW visits, with data stored on the device.

Component 2: Offline Data Storage and Batch Transmission.

Data are stored on the patient device or CHW device during periods without internet access and transmitted to a central cloud server in batches during periods of connectivity. This design removes dependency on continuous network access.

Component 3: Algorithmic Interpretation.

The cloud platform applies validated algorithms, informed by wearable artificial intelligence classification

models where locally recalibrated data permit to HRV, EDA, and cortisol inputs to generate mental health risk scores calibrated against the Patient Health Questionnaire-9 (PHQ-9), the Generalised Anxiety Disorder Assessment-7 (GAD-7), and the Post-Traumatic Stress Disorder Checklist-5 (PCL-5) [11]. Risk thresholds are further aligned with the priority-condition protocols in the WHO mhGAP Intervention Guide, which was specifically designed for clinical decision-making by non-specialist health workers [31]. Outputs are expressed as colour coded risk levels accessible to CHWs without physiological training.

Component 4: Community Health Worker Interface.

The CHW mobile dashboard displays current risk scores, trend data, and scripted response protocols. When a risk threshold is reached, the dashboard generates a specific action: continue monitoring, initiate a first-response protocol, or escalate to remote clinical review.

Component 5: Remote Clinical Oversight.

Flagged cases are reviewed by a psychiatrist or clinical psychologist via telemedicine, building on the growing evidence base for telepsychiatry in resource-constrained African settings [27]. The clinician receives a structured summary of biosensor trends, cortisol values, and symptom history. This component extends specialist oversight to underserved communities without requiring physical presence.

Component 6: Data Governance and Consent Management.

Because continuous physiological data is more sensitive and more identifiable than episodic self-report, the platform embeds explicit, revisitable consent, data minimisation, and defined retention limits from the point of enrolment, in line with the governance objectives of the WHO Global Strategy on Digital Health 2020–2025 and with the regulatory gaps identified in national digital mental health law [29-30].

CHW Workload and Task Integration

A critical operational consideration for the scalability of the mNEMF is the additional workload that may be placed on community health workers (CHWs). Although the framework is designed to use existing CHW programmes rather than establish parallel service structures, adding biosensor management, timed salivary cortisol collection, data recording, and patient follow-up could create task saturation if these activities are introduced as separate administrative responsibilities. This is particularly relevant because CHW density varies substantially across Sub-Saharan African settings, with estimates ranging from 11.2 to 59.5 workers per 10,000 population depending on working arrangements [23]. Consequently, the feasibility of mNEMF implementation depends not only on the availability of devices and connectivity but also on the

extent to which monitoring tasks can be incorporated into established CHW workflows.

To minimise additional time and administrative burden, the mNEMF should be implemented through simplified, standardised protocols that combine monitoring activities with routine home visits and scheduled community contacts. Wearable devices should be configured for straightforward patient use, with CHWs primarily responsible for device placement, brief checks of device function, and troubleshooting rather than repeated manual recording of physiological measurements. Timed salivary cortisol collection should use a short, clearly sequenced protocol with predefined sampling times and minimal documentation requirements. Where possible, patient identifiers, timestamps, physiological readings, and device status should be captured automatically by the mobile application, reducing duplicate paper-based and electronic documentation.

The framework's offline data-storage and batch-transmission component can further reduce workload by allowing CHWs to collect and store information during routine visits without waiting for network connectivity or repeatedly attempting data transmission. Data can subsequently be transmitted automatically in batches when connectivity becomes available. Similarly, automated risk scoring can reduce the need for CHWs to interpret raw HRV, EDA, and cortisol measurements. The colour-coded dashboard should present only the information required for the immediate action continued monitoring, first response, or escalation for remote clinical review thereby limiting cognitive and administrative demands on CHWs.

Integration with existing home-visit procedures should therefore be a core implementation principle of the mNEMF. Where a CHW is already visiting a patient for routine health or psychosocial support, device checks, symptom screening, and scheduled cortisol collection can be incorporated into the same encounter rather than requiring additional visits. Follow-up alerts generated by the platform should be prioritised according to clinical risk so that CHWs do not need to review every patient's physiological data manually. In settings with limited CHW availability, supervisory teams may also allocate monitoring responsibilities according to caseload and risk level, while remote clinicians provide oversight for flagged cases.

These measures are intended to ensure that mNEMF functions as a task-supporting system rather than an additional parallel workload. The operational objective is to replace repetitive manual processes with automated capture, simplified protocols, batch transmission, and risk-based follow-up. Nevertheless, the actual time required for each monitoring activity should be measured during prospective African pilot studies, and implementation protocols should be revised according to observed CHW workload, caseload, training requirements, and patient contact time. This would provide empirical evidence that

the framework improves monitoring capacity without producing unsustainable task saturation.

The mNEMF advances beyond existing African mHealth mental health models by adding continuous physiological measurement, algorithmic risk interpretation aligned to an existing WHO clinical protocol, and an explicit data governance layer to platforms that currently rely entirely on self-report and offer little formal privacy protection. Integration into existing programmes rather than creation of parallel structures is both more efficient and more likely to achieve community trust and sustained use [5,24].

DISCUSSION

The evidence synthesized in this review supports four clear conclusions.

- Firstly, HRV, EDA, and salivary cortisol are valid neuroendocrine markers for the mental health disorders with the highest burden in Sub-Saharan Africa. Their effect sizes are clinically meaningful, their measurement by current wearable devices is validated, and their collection through point-of-care assays is feasible in low-resource field conditions.
- Secondly, the mHealth delivery infrastructure needed to implement continuous neuroendocrine monitoring already exists, unevenly, in urban and peri-urban African communities through smartphone penetration, established CHW programmes, and proven task-sharing platforms [22, 24, 26].
- Thirdly, the barriers to implementation such as connectivity, cost, privacy, and CHW capacity are not insurmountable; each is addressed by a specific design component of the mNEMF.
- Fourthly, the regulatory infrastructure to protect the resulting data is still immature relative to the technical infrastructure to collect it, and closing this gap is a precondition for responsible scale-up rather than a secondary concern [29].

A finding of particular importance is that the interaction between chronic psychosocial adversity and neuroendocrine dysregulation in Sub-Saharan African communities means that HRV and cortisol monitoring will detect a high proportion of clinically relevant cases even in community samples without a prior mental health diagnosis [7-8]. Populations exposed to poverty, displacement, gender-based violence, and HIV carry elevated allostatic loads that produce measurable HPA axis and autonomic dysregulation before clinical symptoms are recognized [10,17-18]. This makes neuroendocrine monitoring particularly valuable as a screening and early detection tool, not only as a follow-up instrument for diagnosed patients.

The cost-effectiveness evidence for task-shared, technology-supported mental health care in low- and middle-income countries strengthens the economic case

for the mNEMF while the persistent gender gap in smartphone and mobile internet access is a reminder that a purely technology-led model risks widening, rather than narrowing, existing inequities in access to mental health monitoring unless deliberately designed against [1,28].

LIMITATIONS

Four limitations of this review must be acknowledged. The narrative review design is subject to publication bias; studies with null findings are underrepresented in indexed databases, which may lead to an overestimate of the sensitivity and specificity of neuroendocrine markers in community monitoring contexts. The evidence base for the specific combination of mHealth and neuroendocrine mental health monitoring in Sub-Saharan Africa is nascent; several conclusions are extrapolated from studies in non-African low-income settings and require confirmation by primary African research.

The mNEMF algorithms must be calibrated against African-specific psychiatric rating scale data to correct for cultural differences in the expression of depression, anxiety, and PTSD before risk thresholds established in non-African populations, including the wearable artificial intelligence models reviewed by are applied. The point-of-care cortisol protocol requires timed salivary sampling, which introduces logistical complexity in hot climates where immunoassay strip stability may be reduced [11-12]. Finally, the regulatory analysis in this review draws primarily on South African case law and policy data governance conclusions may not generalise to jurisdictions with less developed data protection regimes. These limitations must be addressed in a prospective pilot study [29].

CONCLUSION

This paper has established that HRV, EDA, and salivary cortisol are valid neuroendocrine markers for the most prevalent mental health disorders in Sub-Saharan Africa and that current mHealth technology, including emerging wearable artificial intelligence, can capture and interpret these markers in community settings without specialist equipment or personnel [11]. The mNEMF provides an integrated operational model for deploying these tools through community health worker programmes, with offline data storage, algorithmic risk scoring aligned to WHO clinical protocols, remote clinical oversight, and an explicit data governance layer addressing the five implementation barriers identified in the reviewed literature.

The treatment gap for mental health disorders in Sub-Saharan Africa cannot be closed by training more psychiatrists alone. The region lacks the workforce for that approach to reach the 90% of people with mental health disorders who currently receive no care [32]. mHealth neuroendocrine monitoring offers a different pathway: one that uses the technology already present, unevenly, in

affected communities, extends the capacity of existing CHW programmes even where their density varies widely and produces objective physiological data that improve the quality of mental health decisions at every level of the health system, provided that the data governance structures required to protect that information are built in from the outset [23,29]. Piloting and validating the mNEMF in Sub-Saharan African communities is the immediate next step.

RECOMMENDATIONS

Based on the evidence reviewed and the mNEMF proposed in this paper, the following six recommendations are directed to African governments, health ministries, development partners, and research institutions:

- National digital health strategies in Sub-Saharan Africa must be revised to include HRV-capable wearable devices and point-of-care cortisol platforms as approved instruments for community mental health monitoring, in line with the governance objectives of the WHO Global Strategy on Digital Health with procurement criteria that prioritize validated, low-cost devices suitable for field conditions [30].
- The mNEMF must be piloted in a minimum of three countries representing anglophone, francophone, and lusophone contexts within existing CHW mental health delivery programmes such as the Friendship Bench and StrongMinds, with embedded implementation research to generate Africa-specific validation data for neuroendocrine risk thresholds and for locally recalibrated wearable artificial intelligence models [11].
- Community health worker training curricula in countries implementing the mNEMF must include structured modules on wearable device operation, cortisol sampling protocols, and the interpretation of colour coded risk dashboards, drawing on evidence that onsite, intuitively designed digital training is the strongest predictor of adoption [26]. All training materials must be designed for low digital literacy contexts and must not rely on text-heavy clinical documentation. Training and implementation protocols should also emphasise workflow integration, simplified device maintenance, automated data capture, and workload management to minimise task saturation.
- National health research ethics committees, guided by the data protection gaps documented in existing digital mental health law analyses must develop data privacy frameworks specific to continuous physiological monitoring of mental health conditions. These frameworks must address the sensitivity of mental health data in communities where psychiatric stigma is high and must specify consent procedures, data retention limits, and access controls [29].
- Medical and health science universities in Sub-Saharan Africa must include the neuroendocrine physiology of

mental health disorders and the principles of mHealth monitoring in physiology, public health, and psychiatry training programmes, addressing the human resource shortages for mental health care identified across the region and building domestic research and implementation capacity for the next generation of African health professionals [32].

- The Global Mental Health Action Plan 2013–2030 the Africa CDC mental health initiative and development partners active in African health systems must designate specific funding streams for mHealth neuroendocrine monitoring innovation in low-resource African settings, including funding to close the gender gap in mobile technology access recognizing community-based physiological monitoring as a priority frontier in African mental health research [1,6,33].

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