Leveraging Artificial Intelligence to Improve Mental Health Service Delivery: Design and Innovation of the Elevate Minds Network System (EMNS).

Francline O. Owuor[1*], Andrew Kipkebut[2], Francis Mwaniki[3]

Kabarak University, Nakuru

***Corresponding Author**

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ABSTRACT

Mental health disorders represent a major global public health challenge, affecting approximately one in eight individuals worldwide, equivalent to nearly one billion people, yet access to adequate care remains critically limited due to persistent stigma, financial barriers, geographic inaccessibility, and widespread shortages of trained mental health professionals (World Health Organization [WHO], 2022). The global treatment gap for mental health conditions is estimated at more than 75% in low- and middle-income countries (LMICs), where psychiatric and psychological resources are severely under-resourced relative to need (Patel et al., 2018). Digital mental health interventions (DMHIs), particularly those powered by artificial intelligence (AI), offer scalable, affordable, and accessible solutions to bridge this persistent treatment gap (Torous et al., 2021).

This study presents the design, implementation, and preliminary evaluation of the Elevate Minds Network System (EMNS), a hybrid digital mental health platform that integrates an AI-powered conversational chatbot (Elevana AI) with human counseling, peer support networks, and psychoeducational resources. Developed within the context of Kabarak University and piloted with a broader community of adult digital mental health users, EMNS was designed to address the intersecting barriers of accessibility, stigma, and resource scarcity in mental health service delivery.

A convergent mixed-methods research design was employed, combining a quantitative pre–post observational study with qualitative inquiry conducted over a three-month intervention period. Participants ($N = 150$) were assessed using internationally validated standardized instruments, including the Patient Health Questionnaire (PHQ-9), Generalized Anxiety Disorder scale (GAD-7), WHO-5 Well-Being Index, Multidimensional Scale of Perceived Social Support (MSPSS), System Usability Scale (SUS), and Client Satisfaction Questionnaire (CSQ-8). Engagement metrics were analyzed to evaluate system utilization patterns and behavioral indicators of platform adoption.

Statistical analyses included paired-sample t-tests, effect size calculations (Cohen’s d), and regression analysis, while qualitative data from semi-structured interviews were examined using Braun and Clarke’s (2006) six-phase thematic analysis framework. Findings revealed statistically significant reductions in depression symptoms (PHQ-9: $M\Delta = -5.5$, $p < .001$, $d = 1.12$) and anxiety symptoms (GAD-7: $M\Delta = -5.2$, $p < .001$, $d = 1.08$), alongside significant improvements in psychological well-being (WHO-5: $M\Delta = +24.9$, $p < .001$, $d = 1.43$) and perceived social support (MSPSS: $M\Delta = +8.3$, $p < .001$, $d = 0.92$). The platform demonstrated high usability (SUS mean = 79.4) and strong user satisfaction (CSQ-8 mean = 27.1 out of 32). Qualitative themes identified improved accessibility, stigma reduction, enhanced user empowerment, and the complementary value of hybrid AI-human care.

These findings suggest that EMNS constitutes a feasible, acceptable, and potentially effective hybrid model for improving mental health service delivery, particularly in underserved populations. The study contributes foundational evidence to the emerging field of digital psychiatry and AI-augmented mental health care, with significant implications for universities, healthcare systems, governments, and global mental health policy.

Keywords: Artificial Intelligence, Digital Mental Health, Hybrid Care Model, Conversational AI, Mental Health Service Delivery, Chatbot, Teletherapy, Peer Support, Low- and Middle-Income Countries

INTRODUCTION

The global burden of mental health disorders has reached unprecedented proportions in the twenty-first century, constituting one of the most significant yet under-addressed challenges in public health. According to the World Health Organization (WHO, 2022), approximately 970 million people worldwide—nearly one in eight—live with a mental disorder, with depression and anxiety representing the most prevalent conditions. Depression alone affects more than 280 million individuals globally and is the leading cause of disability worldwide, accounting for a substantial proportion of years lived with disability (YLDs) across all regions (GBD 2019 Mental Disorders Collaborators, 2022). The economic cost of untreated mental illness is equally staggering; the WHO estimates that depression and anxiety disorders alone cost the global economy approximately USD 1 trillion annually in lost productivity (WHO, 2022).

Despite this overwhelming burden, the global mental health treatment gap remains unacceptably wide. It is estimated that more than 75% of people with mental disorders in LMICs receive no treatment whatsoever (Patel et al., 2018). Even in high-income countries, fewer than half of individuals with diagnosable mental disorders access formal care (Kohn et al., 2004). This gap is perpetuated by a complex interplay of structural, social, and systemic barriers, including critical shortages of trained mental health professionals, inadequate healthcare infrastructure, geographic inaccessibility, prohibitive treatment costs, and deeply entrenched social stigma (WHO, 2022). In Sub-Saharan Africa, where Kenya is located, the situation is particularly acute: the continent accounts for approximately 14% of the global burden of neuropsychiatric conditions yet possesses less than 1.4 psychiatrists per 100,000 population, compared to a WHO recommended minimum of 1 per 10,000 (Sankoh et al., 2018).

The rapid proliferation of digital technologies and internet connectivity, even in previously underserved regions, has opened transformative new pathways for mental health service delivery. Smartphone adoption in Sub-Saharan Africa exceeded 50% by 2023 (GSMA Intelligence, 2023), and internet penetration in Kenya has surpassed 85% of the population, creating fertile conditions for digital health innovation (Kenya National Bureau of Statistics, 2023). Digital mental health interventions (DMHIs)—encompassing mobile applications, web-based platforms, teletherapy systems, and AI-powered conversational agents—have emerged as promising strategies to extend the reach of mental health support to populations previously excluded from formal care (Torous et al., 2021; Anthes, 2016).

Artificial intelligence, and conversational AI in particular, has attracted considerable scholarly and clinical interest as a mechanism for delivering scalable, low-cost mental health support. AI-powered chatbots such as Woebot, Wysa, and Replika have demonstrated preliminary effectiveness in reducing symptoms of depression and anxiety, improving emotional self-awareness, and facilitating engagement with evidence-based therapeutic strategies such as Cognitive Behavioral Therapy (CBT) (Fitzpatrick et al., 2017; Inkster et al., 2018; Firth et al., 2017). However, standalone AI systems are not without significant limitations. Critics have noted that purely automated mental health tools lack the emotional depth, contextual interpretive capacity, and clinical judgment necessary to address complex or severe psychological presentations (Luxton et al., 2011; Topol, 2019). Moreover, algorithmic bias, data privacy vulnerabilities, and ethical concerns regarding autonomous AI in sensitive healthcare contexts represent important challenges that require careful governance (Obermeyer et al., 2019; Char et al., 2018).

A hybrid model of care—one that combines the scalability and accessibility of AI with the empathy and expertise of human mental health professionals—has been proposed as a more balanced and ethically sound framework for digital mental health service delivery (Mohr et al., 2013; Firth et al., 2020). Such hybrid systems can leverage AI for initial engagement, psychoeducation, and continuous monitoring while ensuring that human professionals remain available for complex assessments, crisis intervention, and the relational dimensions of therapeutic care.

The Elevate Minds Network System (EMNS) was developed within this theoretical and practical context. EMNS is a hybrid digital mental health platform that integrates an AI-powered conversational chatbot (Elevana AI) with virtual human counseling, moderated peer support communities, and a comprehensive psychoeducational resource library. The system was conceptualized and developed at Kabarak University, Nakuru, Kenya, with the explicit purpose of improving mental health service accessibility and delivery for digitally connected adults, with a particular focus on students, young professionals, and underserved community members.

This paper presents the design rationale, system architecture, implementation methodology, and preliminary evaluation findings of the EMNS pilot study. The study contributes to the growing evidence base for hybrid AI-human digital mental health systems and offers theoretical, practical, and policy-relevant insights for healthcare systems, academic institutions, governments, and international mental health organizations. Specifically, it addresses the following research objectives.

Problem statemen

Mental health disorders continue to pose one of the most significant and structurally underaddressed global public health challenges of the twenty-first century. The WHO's World Mental Health Report (2022) confirmed that mental ill-health contributes substantially to disability-adjusted life years (DALYs), reduced economic productivity, family dysfunction, and diminished overall quality of life across all demographic groups and geographic regions. Depression ranks as the single leading cause of disability worldwide, while anxiety disorders collectively affect an estimated 301 million people globally (WHO, 2022). Yet, despite this scale of burden, most affected individuals—particularly those in LMICs—receive no evidence-based treatment whatsoever.

Several deeply entrenched structural and systemic barriers impede effective mental health service delivery. Social stigma remains one of the most formidable obstacles, with individuals frequently postponing or entirely avoiding help-seeking due to fear of discrimination, judgment, and social marginalization (Corrigan, 2004; Clement et al., 2015). In many sub-Saharan African cultural contexts, mental health conditions are associated with spiritual explanations, social shame, or personal weakness, further discouraging individuals from accessing professional support (Ae-Ngibise et al., 2010). The economic barriers to accessing mental health care are equally prohibitive. In Kenya, private psychological services can cost between KES 3,000–8,000 per session, placing sustained therapeutic engagement beyond the financial reach of most citizens (Ministry of Health Kenya, 2021).

The shortage of trained mental health professionals represents a structural crisis of considerable magnitude. Kenya has approximately 90 psychiatrists for a population exceeding 55 million people, yielding a psychiatrist-to-population ratio of fewer than 0.2 per 100,000 (WHO Global Health Observatory, 2022). This severe workforce deficit means that even individuals who actively seek professional support frequently encounter months-long waiting lists, inadequate follow-up care, and absence of crisis response mechanisms. Geographic inaccessibility further compounds this challenge: many specialist mental health services are concentrated in urban centers, leaving rural and peri-urban populations with virtually no access to professional care (Ndetei et al., 2016).

While digital mental health interventions have emerged as promising strategies to address these access barriers, significant limitations remain within existing approaches. Standalone AI chatbots, though scalable and available around the clock, frequently lack the emotional intelligence, contextual sophistication, and clinical judgment required to support individuals with moderate-to-severe mental health presentations (Luxton et al., 2011). Conversely, conventional teletherapy models, while clinically rigorous, are constrained by professional availability, cost, and the challenges of maintaining therapeutic continuity in resource-limited settings. There is consequently a critical and evidence-supported need for an integrated, scalable, ethically governed, and user-centered mental health solution capable of combining the accessibility of digital AI technologies with the emotional depth and clinical oversight of human professionals (Mohr et al., 2013; Firth et al., 2020).

Furthermore, the evidence base for hybrid AI-human digital mental health systems remains nascent, particularly within African and LMIC contexts. Existing studies have predominantly been conducted in high-income Western settings, limiting the generalizability of findings to populations experiencing different socio-cultural, infrastructural, and epidemiological contexts (Naslund et al., 2017). There is therefore an urgent need for empirically grounded studies that evaluate hybrid digital mental health platforms within LMIC settings, generating context-specific evidence to inform system development, policy, and implementation.

The Elevate Minds Network System (EMNS) was specifically designed to address these identified gaps. However, empirical evaluation of its usability, acceptability, and preliminary effectiveness is required before large-scale deployment can be responsibly pursued. This study responds directly to that imperative.

Objective

The primary objective of this study was to develop and conduct a preliminary evaluation of the Elevate Minds Network System (EMNS) as a hybrid digital mental health platform that integrates artificial intelligence with human-centered psychological support services.

The following specific objectives guided the study:

1. To examine whether engagement with EMNS was associated with measurable reductions in depression symptoms, as assessed by the PHQ-9, over a three-month intervention period.

2. To explore whether EMNS engagement was associated with reductions in anxiety symptoms, measured using the GAD-7 instrument.

3. To determine whether interaction with the EMNS platform was associated with improvements in psychological well-being, assessed using the WHO-5 Well-Being Index.

4. To assess whether EMNS participation enhanced users perceived social support, as measured by the Multidimensional Scale of Perceived Social Support (MSPSS).

5. To evaluate user engagement patterns, platform usability, and overall satisfaction using behavioral metrics, the System Usability Scale (SUS), and the Client Satisfaction Questionnaire (CSQ-8).

6. To explore user and provider experiences, perceptions, and challenges through semi-structured qualitative interviews, generating thematic insights regarding platform acceptability and areas for improvement.

7. To assess the scalability potential and contextual applicability of EMNS across diverse user populations and settings.

LITERATURE REVIEW

The Global Mental Health Burden and Service Delivery Gaps

The global prevalence of mental health disorders has been extensively documented across epidemiological literature. The Global Burden of Disease study (GBD 2019 Mental Disorders Collaborators, 2022) identified mental disorders as collectively accounting for approximately 15.9% of all non-fatal disease burden globally. Depression and anxiety disorders alone generate an estimated 1.1 billion disability-adjusted life years (DALYs) annually, surpassing the combined burden of HIV/AIDS, tuberculosis, and malaria. Despite this immense burden, mental health systems globally remain critically underfunded: governments allocate an average of only 2% of national health budgets to mental health, and in many LMICs, this figure falls below 1% (WHO, 2022).

Kessler and Ustun (2008) established that even in high-income countries with established psychiatric infrastructure, fewer than 40% of individuals with serious mental disorders receive minimally adequate care. In LMICs, this proportion drops to below 10%, creating what has been widely termed the “global mental health treatment gap” (Patel et al., 2018). This gap is not merely a consequence of resource scarcity but reflects complex intersecting dynamics of stigma, workforce inadequacies, health system fragmentation, and socio-cultural barriers to help-seeking. In Kenya specifically, the National Mental Health Policy (2015–2030) acknowledges that mental health services are insufficiently integrated into the primary healthcare system, resulting in inadequate community-level mental health support (Ministry of Health Kenya, 2021).

Digital Mental Health Interventions: A Paradigm Shift in Service Delivery

The emergence of digital mental health interventions (DMHIs) over the past two decades has fundamentally altered the landscape of mental health service delivery. DMHIs encompass a broad and heterogeneous category of digital tools, including smartphone applications, web-based therapeutic programs, virtual reality environments, wearable sensor platforms, and AI-powered conversational agents (Torous & Roberts, 2017). Systematic reviews and meta-analyses have consistently demonstrated that DMHIs can effectively reduce symptoms of depression, anxiety, and stress, with effect sizes comparable to traditional face-to-face interventions in appropriately selected populations (Linardon et al., 2020; Lim et al., 2022).

A landmark meta-analysis by Linardon et al. (2020) encompassing 66 randomized controlled trials and over 8,000 participants found a mean effect size of $g = 0.56$ for smartphone interventions targeting depression and anxiety, which the authors classified as a moderate-to-large effect comparable to that of brief face-to-face psychological interventions. Subsequent reviews have confirmed these findings across diverse cultural and clinical populations (Lim et al., 2022; Wozney et al., 2017). The specific advantages of DMHIs include 24/7 availability, anonymity, elimination of transportation barriers, reduced stigma associated with help-seeking, and capacity for adaptive personalization through machine learning algorithms (Torous et al., 2021).

However, the evidence base for DMHIs is not without methodological limitations. Studies have frequently been criticized for small sample sizes, high attrition rates, short follow-up periods, and inadequate attention to implementation context (Baumeister et al., 2014). A significant challenge in the field is the substantial gap between the proliferation of mental health applications—the Apple App Store alone lists over 20,000 mental health-related applications—and the limited number with robust peer-reviewed evidence of clinical effectiveness (Linardon et al., 2020). Regulatory frameworks governing DMHI safety and efficacy remain underdeveloped in most jurisdictions, raising important questions about user safety, clinical standards, and accountability.

Artificial Intelligence in Mental Health: Opportunities and Challenges

Artificial intelligence, particularly in the form of natural language processing (NLP), machine learning (ML), and deep learning architectures, has emerged as a transformative technological force in mental health care (Shatte et al., 2019; Graham et al., 2019). AI applications in mental health span a wide continuum, from predictive analytics and automated screening algorithms to conversational agents, sentiment analysis tools, and personalized intervention delivery systems. The application of AI holds particular promise for addressing mental health workforce shortages by enabling the delivery of evidence-based psychological support at scale, without proportional increases in human resource requirements (Topol, 2019).

Conversational AI agents designed specifically for mental health applications have attracted considerable research attention. The most extensively studied example is Woebot, a fully automated CBT-based chatbot evaluated in a randomized controlled trial by Fitzpatrick et al. (2017). This seminal study found that participants randomized to Woebot experienced significantly greater reductions in depression and anxiety symptoms compared to a control group receiving information about mental health resources, with effects emerging over as few as two weeks. Subsequently, Inkster et al. (2018) evaluated Wysa, an AI-powered emotional support tool, and found significant reductions in PHQ-9 depression scores among users with moderate-to-severe depression who engaged consistently with the platform. These studies collectively suggest that well-designed AI conversational agents can function as effective and acceptable components of mental health support systems.

The mechanisms through which AI chatbots may achieve therapeutic effects are theoretically grounded in established psychotherapeutic principles. CBT-based chatbots promote cognitive restructuring by guiding users to identify and challenge maladaptive thought patterns, while mindfulness-based applications facilitate present-moment awareness and emotional regulation. The consistent availability and judgment-free interaction style of

AI agents may also reduce the activation energy required for initial help-seeking, creating a low-barrier entry point into the mental health care system (Fulmer et al., 2018).

Nevertheless, AI systems in mental health applications face significant technical, ethical, and clinical challenges. Current NLP systems, despite substantial advances through large language model architectures, frequently struggle with nuanced emotional interpretation, cultural context sensitivity, and the recognition of complex or ambiguous psychological presentations (Luxton et al., 2011; Miner et al., 2016). Studies have documented instances of AI chatbots generating clinically inappropriate responses to disclosures of suicidal ideation, underscoring the critical importance of robust crisis detection and escalation mechanisms (Miner et al., 2016). Algorithmic bias—whereby AI systems perform differently across demographic groups due to unrepresentative training data—represents an additional equity concern with direct implications for mental health application (Obermeyer et al., 2019).

Hybrid AI-Human Models: Theoretical and Empirical Foundations

The limitations of both standalone AI systems and conventional human-delivered services have prompted growing scholarly interest in hybrid models of care that integrate AI capabilities with human clinical oversight. Mohr et al.'s (2013) conceptual framework for behavioral intervention technologies (BITs) articulates the theoretical rationale for hybrid systems, proposing that digital elements should be strategically combined with human support components in a manner that optimizes clinical outcomes, user engagement, and resource efficiency. This framework has been subsequently refined into a "supportive accountability" model, which posits that human oversight of digital interventions significantly improves engagement and adherence (Mohr et al., 2011).

Empirical evidence for hybrid AI-human systems has grown substantially in recent years. A meta-analysis by Lim et al. (2022) found that digitally delivered mental health interventions incorporating some form of human support element demonstrated significantly higher effect sizes ($g = 0.68$) than fully automated programs ($g = 0.41$), particularly for outcomes related to depression and anxiety. The mechanisms underlying this differential effectiveness appear to involve enhanced therapeutic alliance, improved motivation and accountability, and the capacity for human coaches or therapists to address individual-specific barriers to engagement that automated systems cannot anticipate.

Firth et al. (2020) conducted a comprehensive review of hybrid digital psychiatry models and concluded that the most evidence-based and ethically sound approach to digital mental health service delivery involves AI functioning as a support and augmentation tool for human clinicians rather than as an autonomous therapeutic agent. This model—which the authors termed "clinician-augmented AI"—allows artificial intelligence to handle task-repetitive aspects of mental health care such as psychoeducation delivery, symptom monitoring, appointment scheduling, and initial triage, while reserving complex clinical judgment, therapeutic relationship building, and crisis management for trained human professionals.

Digital Mental Health in Low- and Middle-Income Countries

The potential of DMHIs to address mental health service gaps in LMICs has attracted increasing research attention, though the evidence base remains less developed compared to high-income country contexts. Naslund et al. (2017) conducted a systematic review of digital mental health interventions in LMICs and concluded that while existing evidence was generally promising, most studies were conducted in a limited number of countries and settings, with significant heterogeneity in intervention design, outcome measurement, and implementation approach. The review identified critical gaps in evidence regarding the appropriateness of DMHIs developed in high-income countries when applied to LMIC socio-cultural and infrastructural contexts.

Subsequent research has explored the specific contextual adaptations required for digital mental health tools to be effective and culturally acceptable in African settings. Agyapong et al.'s (2018) randomized controlled trial in Ghana demonstrated that text message-based mental health support significantly improved depressive symptom severity and medication adherence among individuals with major depressive disorder. Similarly, Gureje et al.'s (2020) systematic review highlighted the importance of integrating community-based components into digital mental health interventions to align with African Ubuntu philosophies of collective well-being and social interconnectedness.

The specific context of Kenyan higher education institutions presents unique mental health challenges that digital interventions may be particularly well-positioned to address. A national study of mental health among Kenyan university students (Straud et al., 2019) found that over 30% of respondents reported clinically significant depression symptoms, while approximately 20% endorsed anxiety disorders. Barriers to accessing university counseling services—including stigma, limited appointment availability, and lack of awareness of available services—were identified as primary obstacles to help-seeking. Digital platforms that address these specific barriers may therefore have particular impact within this population.

Peer Support in Digital Mental Health Systems

The integration of peer support mechanisms into digital mental health platforms represents an increasingly recognized strategy for enhancing both clinical outcomes and social inclusion. Pfeiffer et al.'s (2011) meta-analysis of peer support interventions for depression found a significant overall effect (d = 0.26) on depressive symptoms, with particular benefits observed for individuals who had previously experienced inadequate engagement with formal mental health services. The mechanisms of peer support are theorized to involve social learning, normalization of mental health experiences, recovery hope, and the development of a supportive community identity that counteracts the isolation frequently experienced by individuals with mental health conditions.

In digital environments, peer support is typically delivered through moderated online communities, discussion forums, group messaging systems, and structured peer-facilitated support programs (Naslund et al., 2016). Research by Naslund et al. (2016) on the use of social media platforms by individuals with serious mental illness found that users reported significant benefits from peer interactions, including reduced isolation, improved self-efficacy for illness management, and enhanced hope for recovery. However, unmoderated peer support environments carry documented risks, including exposure to distressing content, peer contagion of self-harm behaviors, and conflicts within online communities, underscoring the importance of professional moderation in digital peer support implementations (Berry et al., 2017).

Ethical and Governance Frameworks for AI in Mental Health

The application of AI in mental health care raises profound ethical questions that must be systematically addressed in system design and governance. Ethical frameworks for AI in healthcare commonly address principles of beneficence, non-maleficence, autonomy, justice, and explicability (Floridi et al., 2018; Jobin et al., 2019). In mental health contexts, these principles acquire particular salience given the vulnerability of the populations involved, the sensitivity of the data collected, and the potential consequences of algorithmic errors on individual well-being and safety.

Data privacy and security represent foundational ethical requirements for AI-powered mental health systems. Mental health data are among the most sensitive categories of personal information, with potential for significant harm—including employment discrimination, relationship damage, and social marginalization—if disclosed without consent. Regulatory frameworks including the General Data Protection Regulation (GDPR) in the European Union and Kenya's Data Protection Act (2019) establish legal obligations regarding the collection, storage, processing, and sharing of personal health data, including through digital platforms (Kenya Data Protection Act, 2019). Compliance with these frameworks is not merely a legal requirement but an ethical imperative in the design of digital mental health systems.

Informed consent in digital mental health contexts presents challenges compared to traditional clinical settings. Users of AI mental health applications may have limited understanding of the nature of data collected, how AI systems process and respond to their inputs, the limitations of automated responses, and the mechanisms for escalation to human professionals. Ensuring genuine informed consent—rather than mere acceptance of opaque terms-of-service agreements—requires deliberate design effort and ongoing communication (Luxton et al., 2011). The EMNS platform addressed this challenge through a structured onboarding process that provided clear, accessible explanations of system functionality, AI limitations, data handling practices, and escalation procedures.

Algorithmic bias in AI mental health applications represents a justice concern with direct implications for equity in mental health care. AI systems trained predominantly on data from high-income, Western, English-speaking populations may perform less effectively for users from diverse cultural, linguistic, and demographic backgrounds (Obermeyer et al., 2019). Addressing this bias requires deliberate attention to training data diversity, regular performance auditing across demographic subgroups, and the integration of cultural competency principles into AI system design (Char et al., 2018).

THEORETICAL FRAMEWORK

This study is grounded in three complementary theoretical frameworks that collectively inform the design, implementation, and evaluation of EMNS.

The Technology Acceptance Model (TAM), originally proposed by Davis (1989) and subsequently extended by Venkatesh and colleagues, provides a foundational framework for understanding user adoption of digital health technologies. TAM posits that perceived ease of use and perceived usefulness are the primary determinants of behavioral intention to use a technology, which in turn predicts actual system use. In the context of EMNS, TAM guided the prioritization of user-centered interface design and the selection of usability (SUS) and satisfaction (CSQ-8) as core outcome measures. The study predicted that higher perceived usability and usefulness would be associated with sustained platform engagement.

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), developed by Venkatesh et al. (2012), extends TAM by incorporating additional determinants of technology adoption including hedonic motivation, social influence, and habit formation. These constructs are particularly relevant in the context of mental health applications, where emotional resonance, peer norms regarding help-seeking, and habitual patterns of self-care behavior are important influences on sustained engagement. UTAUT2 informed the design of EMNS’s peer support and community components, which were intended to harness positive social influence and normalize digital mental health help-seeking.

The Behavioral Intervention Technology (BIT) Model (Mohr et al., 2013) provides the most directly applicable theoretical framework for EMNS’s hybrid design architecture. The BIT model conceptualizes digital mental health interventions as systems comprising “behavioral intervention elements” delivered through “technology platforms,” with the potential for human support to be integrated at multiple points in the care pathway. The model specifically addresses the roles of different BIT components—including automated delivery systems, human coaches, and clinical professionals—in optimizing outcomes for specific target populations. This framework directly informed the multi-component architecture of EMNS and the intentional structuring of Elevana AI as an initial engagement and triage mechanism that transitions users toward human counseling when clinically indicated.

CONCEPTUAL FRAMEWORK

The conceptual framework for this study, illustrated in Figure 1, operationalizes the theoretical foundations described above into a model of how EMNS is hypothesized to improve mental health outcomes. The framework posits that the EMNS platform, through its integrated components of AI chatbot interaction, virtual human counseling, peer support participation, and psychoeducational resource access, produces proximal outcomes of improved platform engagement, reduced stigma, and enhanced help-seeking intention. These proximal outcomes, in turn, mediate the relationship between platform use and distal outcomes of reduced depression and anxiety symptoms, improved psychological well-being, and enhanced perceived social support. User-level factors—including digital literacy, baseline mental health status, and prior help-seeking behavior—are theorized as moderators of this relationship. Contextual factors—including internet connectivity, institutional support, and cultural attitudes toward mental health—are conceptualized as environmental moderators that influence both platform adoption and outcome magnitude.

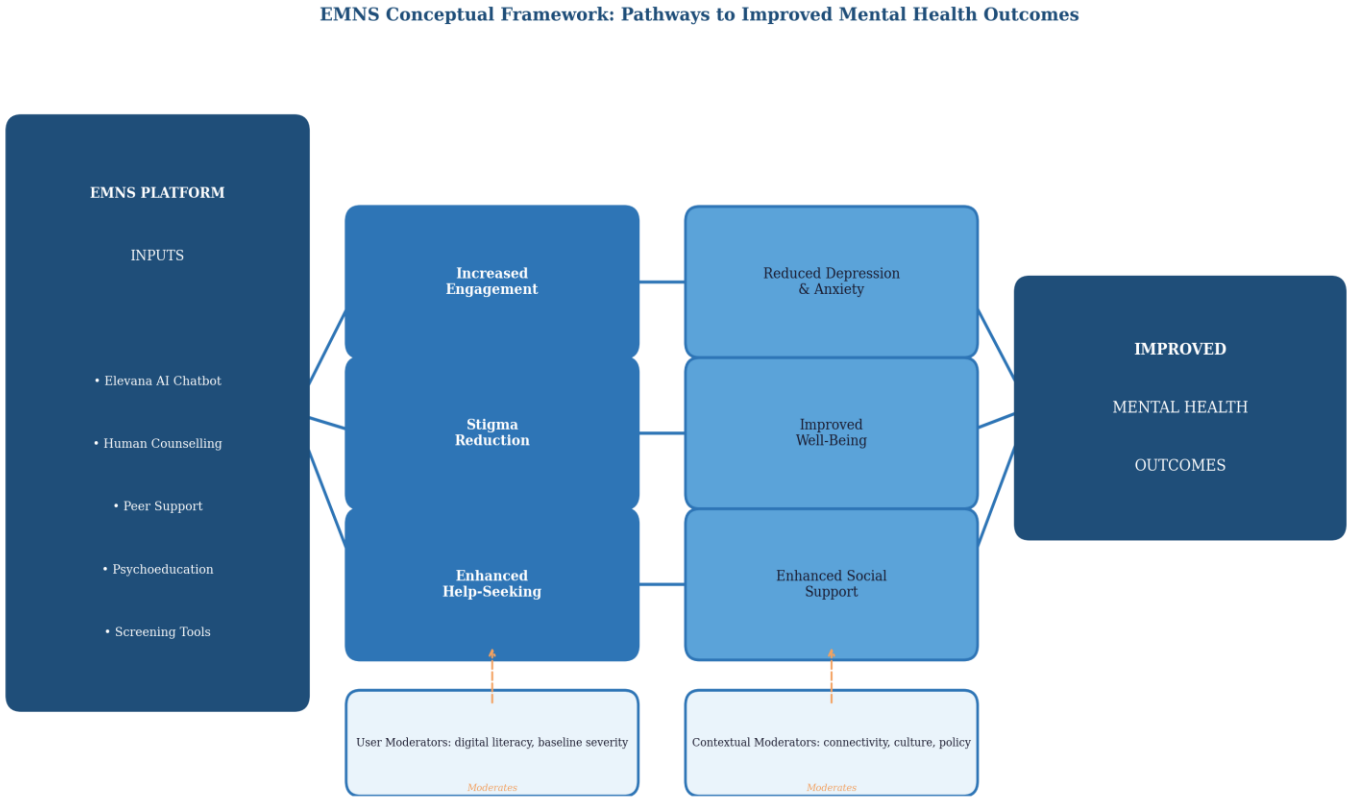

Figure 1. Conceptual framework illustrating the hypothesized pathways through which EMNS engagement produces improvements in mental health outcomes, mediated by proximal platform-level and user-level factors.

METHODOLOGY

Research Design

This study employed a convergent mixed-methods research design to evaluate the design, deployment, usability, acceptability, and preliminary performance of the Elevate Minds Network System (EMNS) (Creswell & Plano Clark, 2018; Torous et al., 2021). The mixed-methods approach was selected because digital mental health interventions involve complex interactions between technology, human behavior, emotional experience, and clinical support systems. Quantitative methods alone would not sufficiently capture the subjective experiences of users interacting with AI-driven support systems, while qualitative methods alone would not provide measurable evidence regarding usability, engagement, and mental health outcome trends. Integrating both methodological traditions through a convergent design enabled a more comprehensive, contextually grounded, and methodologically rigorous evaluation of the EMNS platform (Creswell & Plano Clark, 2018).

The quantitative component adopted a pre–post observational design conducted over a three-month intervention period (Thabane et al., 2010; Harris et al., 2006). Participants completed standardized assessments before actively engaging with the platform and at the conclusion of the three-month period, enabling the examination of changes in depression symptoms, anxiety levels, psychological well-being, perceived social support, and user satisfaction. This design was considered appropriate for the current phase of the project because EMNS is an emerging digital health intervention requiring feasibility testing and exploratory evaluation prior to large-scale randomized controlled trials. The three-month duration was selected based on evidence from digital mental health literature indicating that meaningful patterns of engagement and preliminary psychological change can be observed within this timeframe (Linardon et al., 2020; Thabane et al., 2010).

The qualitative component involved semi-structured interviews with selected participants and mental health professionals who interacted with the system throughout the intervention period (Braun & Clarke, 2006; Patton, 2015). The integration of quantitative and qualitative findings through methodological triangulation strengthened the validity, reliability, and interpretability of the study's conclusions (Lincoln & Guba, 1985; Creswell & Plano Clark, 2018).

Philosophical Foundation

The study was guided by the pragmatic research paradigm, which emphasizes the use of multiple methods to address complex real-world problems without adherence to the epistemological constraints of either positivism or interpretivism alone (Creswell & Plano Clark, 2018). Pragmatism was considered appropriate because the research focused on solving practical challenges associated with mental health service accessibility, digital intervention delivery, and user engagement in a specific socio-cultural and institutional context. The pragmatic paradigm supports the integration of objective quantitative measurements with subjective qualitative experiences, enabling researchers to understand not only whether an intervention produces measurable effects but also how users experience and interpret those effects within their lived contexts.

The study additionally incorporated principles of human-centered design and participatory digital health development. Human-centered approaches emphasize the importance of designing technologies that align with the emotional, psychological, and behavioral needs of end users, particularly those belonging to vulnerable populations. Since mental health systems directly interact with individuals experiencing psychological distress, the principles of usability, empathy, trust, cultural sensitivity, and psychological safety were treated as foundational design requirements throughout the development and evaluation of EMNS.

Study Setting

The study was conducted entirely within the digital environment of the Elevate Minds Network System (EMNS), a web-based mental health platform accessible through smartphones, tablets, laptops, and desktop computers connected to the internet (WHO, 2019). The online setting was intentionally selected to reflect the growing role of telehealth systems and digital health technologies in improving access to mental health support services globally, particularly in LMIC contexts where digital connectivity is expanding rapidly but mental health infrastructure remains underdeveloped (WHO, 2022; GSMA Intelligence, 2023).

The EMNS platform functioned as an integrated digital ecosystem comprising several interconnected and mutually reinforcing components: (a) the Elevana AI conversational chatbot; (b) virtual counseling and teletherapy services; (c) peer support and community engagement systems; (d) a psychoeducational resource repository; (e) mental health screening and assessment tools; (f) appointment booking and scheduling systems; and (g) user engagement monitoring mechanisms. The platform operated with continuous service availability, enabling users to access support at any time of day or night, independent of professional working hours or geographic location.

Target Population, Sampling, and Eligibility Criteria

The target population consisted of adults actively seeking mental health support through digital platforms and online mental health interventions (Rickwood et al., 2005; Torous et al., 2021). Participants included university students, young adults, employed individuals, and members of the general public who voluntarily registered with and interacted with EMNS. This population was selected because research consistently indicates that younger, digitally connected populations represent both the highest-burden demographic for mental health conditions and the cohort most amenable to digital health intervention adoption (Torous et al., 2021; Naslund et al., 2017).

The study employed purposive sampling to recruit participants actively engaging with the EMNS platform (Patton, 2015; Palinkas et al., 2015). For the quantitative component, a target sample of 150–200 active users was established, consistent with recommendations for pilot and feasibility studies in digital mental health (Julious, 2005; Thabane et al., 2010). For the qualitative component, 20–30 participants were selected using maximum variation purposive sampling to ensure diversity across demographic characteristics, engagement frequency, mental health presentation severity, and platform usage patterns. Data collection proceeded until thematic saturation was achieved.

Inclusion criteria: Participants were eligible if they were aged 18 years or older, possessed access to an internet-enabled digital device, had registered as active EMNS users, demonstrated willingness to participate voluntarily, provided electronic informed consent, and were capable of comprehending and completing online assessments in English or Swahili over the three-month study period.

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Exclusion criteria: Participants were excluded if they required immediate psychiatric hospitalization, demonstrated severe psychiatric instability necessitating urgent clinical intervention, were unable to meaningfully interact with the digital platform, failed to complete baseline assessments, or declined to provide informed consent. These criteria were designed to ensure participant safety and the integrity of the data collected.

System Architecture and Description of the Intervention

The Elevate Minds Network System (EMNS) is a hybrid digital mental health platform engineered to integrate artificial intelligence technologies with human-centered mental health support services (Mohr et al., 2013; WHO, 2019). The system architecture was designed according to a layered service delivery model in which AI-driven components provide continuous first-line support and triage, while human professionals remain available for complex clinical assessment, crisis management, and in-depth therapeutic engagement.

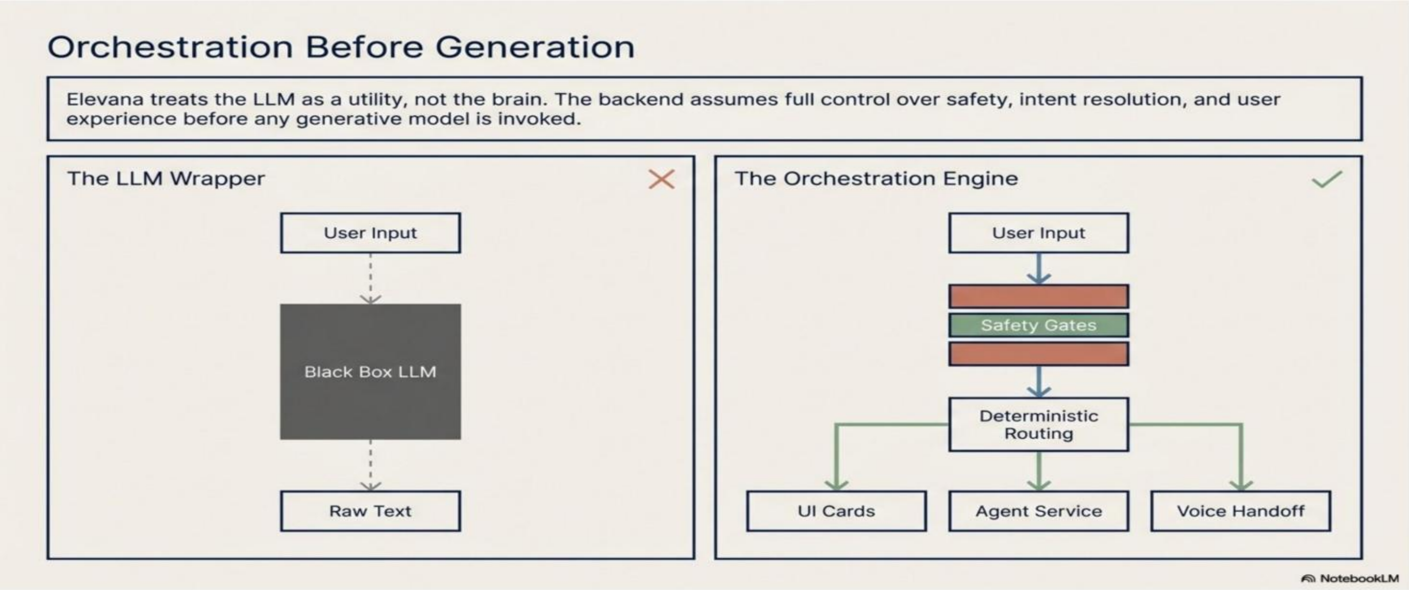

Figure 2. Elevana AI Orchestration Architecture: safety-gated, deterministic routing that treats the language model as a utility, ensuring clinical safety and intent resolution precede any generative output.

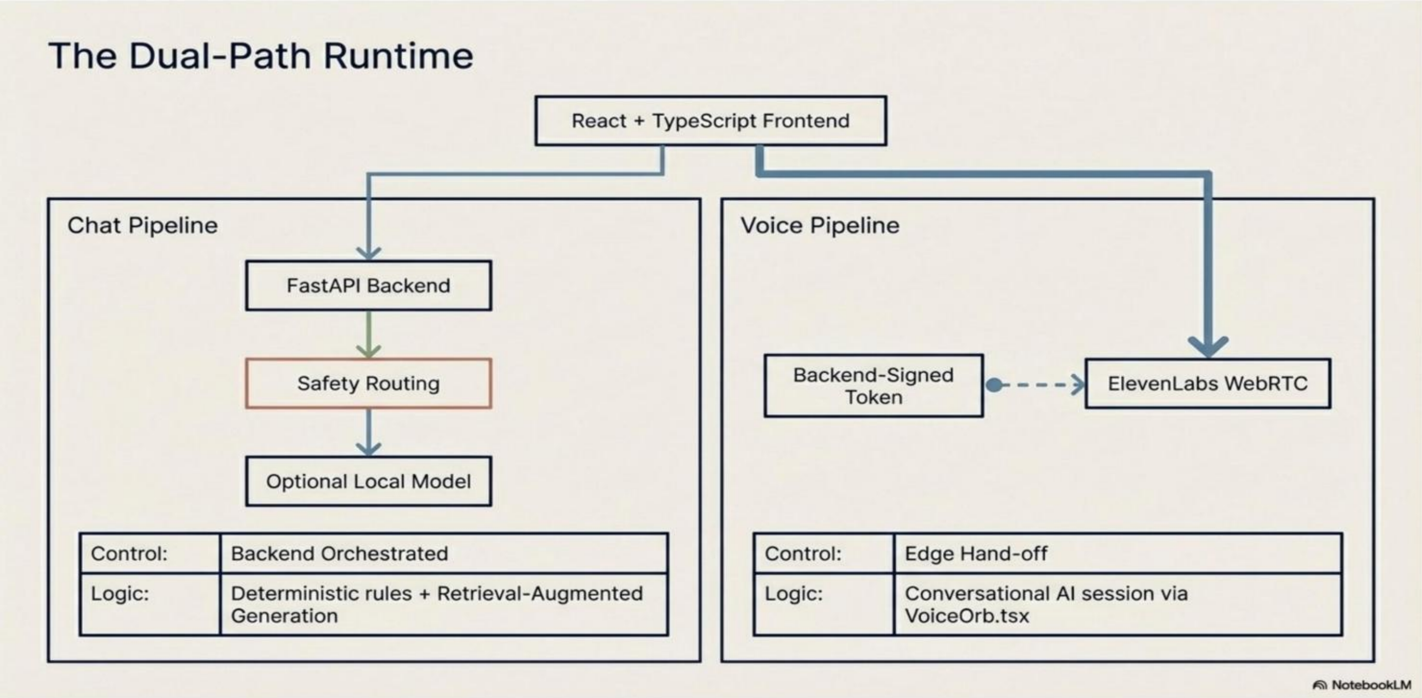

Figure 3. Elevana Dual-Path Runtime Architecture: parallel chat pipeline (FastAPI backend with safety routing) and voice pipeline (ElevenLabs WebRTC), both orchestrated from the React + TypeScript frontend.

Elevana AI Chatbot: Technical Architecture and NLP Functionality

The Elevana AI chatbot functions as the primary entry point into the EMNS ecosystem, providing continuous, 24/7 conversational mental health support through Natural Language Processing (NLP) and machine learning technologies. The chatbot is architecturally grounded in a transformer-based language model fine-tuned on curated mental health dialogue datasets, clinical psychoeducation content, and empirically validated CBT and mindfulness-based intervention scripts. The NLP pipeline incorporates multiple processing layers, including intent classification, sentiment analysis, named entity recognition (for identifying mental health-relevant disclosures), and context-aware response generation.

The Elevana system employs a multi-stage conversation management framework. In the initial interaction phase, the chatbot conducts a structured assessment of the user's current emotional state, presenting standardized screening questions to identify individuals who may require escalation to human counseling or crisis services. Sentiment analysis algorithms continuously monitor conversation tone, flagging significant negative emotional shifts or disclosures of self-harm ideation for immediate human review. The system maintains conversation history within each session and across sessions, enabling context-aware responses that acknowledge previously disclosed information and track changes in user emotional state over time.

The chatbot delivers evidence-based therapeutic content through structured intervention modules encompassing CBT-based thought restructuring exercises, guided mindfulness and relaxation protocols, behavioral activation strategies, and sleep hygiene psychoeducation. Each module is designed with adaptive branching logic, adjusting content complexity and emotional tone based on user responses and engagement level. Crisis detection algorithms trigger automatic escalation protocols when specific risk indicators are identified, immediately notifying available human counselors and providing users with emergency mental health resources.

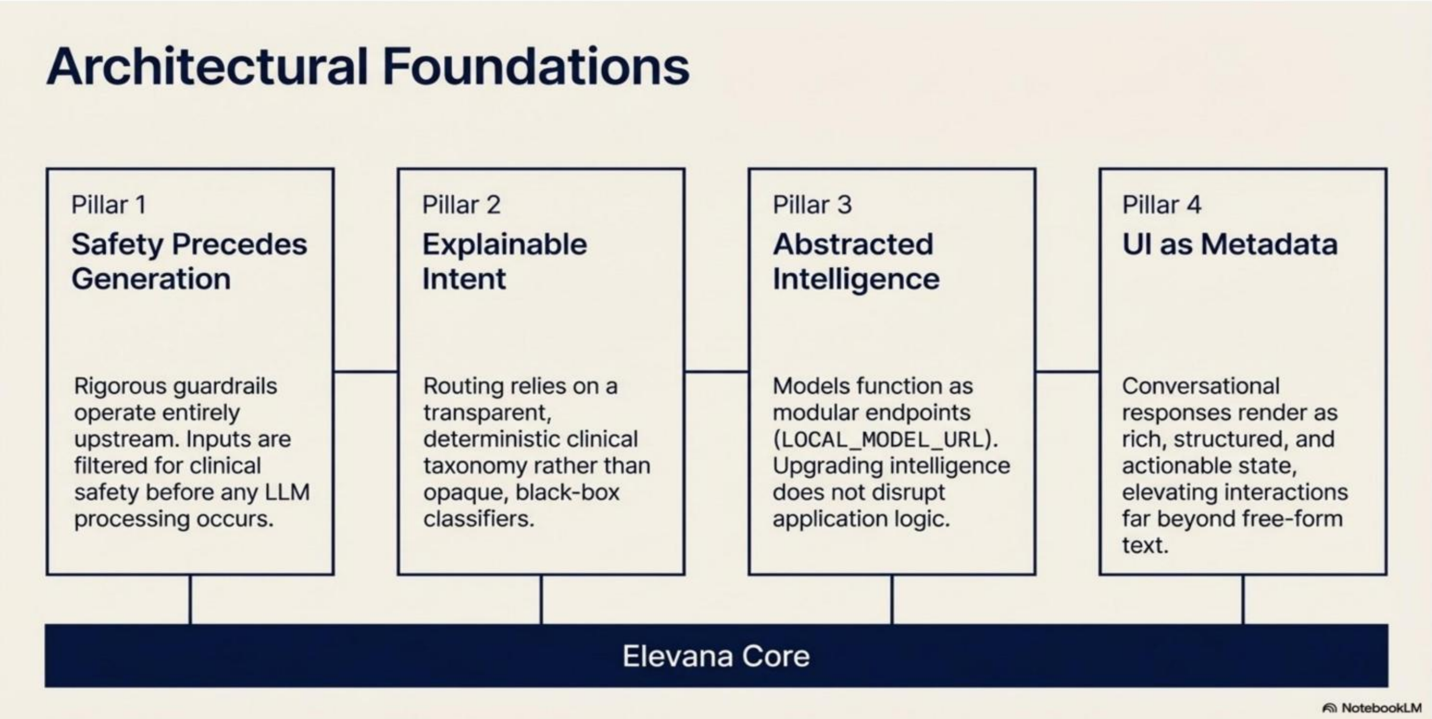

Figure 1Figure 4. Elevana Architectural Foundations: four design pillars (Safety Precedes Generation, Explainable Intent, Abstracted Intelligence, UI as Metadata) grounding all platform components on the Elevana Core.

Human Counseling Services

The human counseling component constitutes the clinical backbone of the EMNS hybrid care model, ensuring that AI-mediated support is anchored within a professionally supervised framework. Licensed counselors and mental health professionals provide structured virtual support through multiple modalities: synchronous video counseling sessions, voice call consultations, live text-based counseling, group therapy sessions, and asynchronous messaging consultations. All counselors engaged through the platform hold relevant professional qualifications and are subject to clinical supervision and ongoing professional development requirements.

The integration of human counseling within the EMNS ecosystem is governed by a structured care pathway framework. Users who engage primarily with Elevana AI are automatically prompted to schedule a human counseling session after a specified number of interactions, ensuring that individuals with ongoing mental health needs receive professional oversight beyond automated support. Counselors have access to AI-generated session summaries and engagement analytics, enabling informed clinical decision-making and continuity of care across AI and human service touchpoints.

Peer Support and Community Engagement

The peer support module enables users to participate in moderated support groups where they share experiences, coping strategies, emotional encouragement, and recovery narratives within a psychologically safe environment (Pfeiffer et al., 2011; Naslund et al., 2016). The module is structured around topically organized communities addressing specific mental health themes, including depression support, anxiety management, grief and loss, academic stress, and workplace well-being. All communities are actively moderated by trained peer support facilitators and overseen by qualified mental health professionals to ensure psychological safety, respectful communication, and adherence to community guidelines.

Psychoeducational Resource Library

The resource library provides users with a curated repository of evidence-based psychoeducational content, including mental health awareness materials, stress management guides, anxiety and depression coping strategies, wellness articles, motivational content, self-help exercises, emotional resilience programs, and sleep hygiene guidance. Resources are organized by mental health topic, user age group, and engagement level, enabling personalized content recommendations based on individual user profiles and engagement history. All materials are reviewed by qualified mental health professionals to ensure clinical accuracy, cultural appropriateness, and accessibility.

Data Collection Procedures

Baseline Assessment Phase

Participants completed comprehensive baseline assessments immediately after registration and platform onboarding. Demographic data collected included age, gender, educational background, employment status, residential location, prior mental health support experiences, and baseline digital device usage patterns. All standardized psychological assessment instruments—PHQ-9, GAD-7, WHO-5, and MSPSS—were administered electronically through the platform's integrated assessment module, with automated scoring and secure data storage.

Engagement and Intervention Phase

During the three-month intervention period, participants interacted with EMNS components according to their individual needs and preferences. Automated system-generated engagement data were continuously collected, encompassing frequency of Elevana AI chatbot interactions, counseling session attendance, duration and frequency of peer support participation, resource library access patterns, and overall platform login frequency. These behavioral metrics provided objective, non-reactive indicators of user engagement that complemented the self-reported assessment data.

Follow-Up Assessment and Qualitative Interview Phase

At the conclusion of the three-month intervention period, participants completed follow-up assessments using the identical standardized instruments administered at baseline, enabling pre–post comparison of mental health indicators. Semi-structured qualitative interviews were subsequently conducted virtually with a purposively selected subsample of 25 participants and five mental health counselors who had been actively involved in platform delivery. Interviews were conducted in English and Swahili, audio-recorded with participant consent, and professionally transcribed. Interview guides explored user satisfaction, perceived chatbot usefulness, emotional experiences during interaction, accessibility and convenience, trust in the system, perceived strengths and challenges, and suggestions for improvement.

Research Instruments

The study utilized six internationally validated standardized instruments with established psychometric properties:

PHQ-9 (Patient Health Questionnaire-9): The PHQ-9 assesses depression severity through nine items corresponding to DSM-5 diagnostic criteria for major depressive disorder, each rated on a 4-point Likert scale (0–3). Total scores range from 0 to 27, with validated cut-offs for minimal (0–4), mild (5–9), moderate (10–14), moderately severe (15–19), and severe (20–27) depression (Kroenke et al., 2001). The PHQ-9 demonstrates strong internal consistency ($\alpha = .89$) and adequate convergent validity with clinical interview-based depression diagnoses.

GAD-7 (Generalized Anxiety Disorder-7): The GAD-7 measures anxiety severity through seven items assessing common symptoms of generalized anxiety disorder over the preceding two weeks (Spitzer et al., 2006). Total scores range from 0 to 21, with validated cut-offs for minimal (0–4), mild (5–9), moderate (10–14), and severe (≥ 15) anxiety. The scale demonstrates high internal consistency ($\alpha = .92$) and good convergent validity with structured clinical interviews.

WHO-5 Well-Being Index: The WHO-5 is a five-item self-report measure of subjective psychological well-being, with total scores converted to a 0–100 scale (World Health Organization, 1998). Scores below 50 indicate poor well-being, and the instrument is widely used as a screening tool for depression risk. The WHO-5 demonstrates good internal consistency ($\alpha = .83$) and sensitivity to change following psychological intervention.

MSPSS (Multidimensional Scale of Perceived Social Support): The MSPSS assesses perceived social support across three subscales—family, friends, and significant other—through 12 items rated on a 7-point Likert scale (Zimet et al., 1988). Total scores range from 12 to 84, with higher scores indicating greater perceived social support. The scale demonstrates strong internal consistency ($\alpha = .88$) and adequate test-retest reliability.

SUS (System Usability Scale): The SUS provides a standardized 10-item measure of system usability applicable across diverse digital platforms (Brooke, 1996). Scores above 68 indicate above-average usability, while scores above 80 indicate excellent usability. The SUS is the most widely used usability measure in human-computer interaction research, with extensive normative data enabling benchmarking against comparable systems.

CSQ-8 (Client Satisfaction Questionnaire): The CSQ-8 measures client satisfaction with services received through eight items rated on a 4-point Likert scale, with total scores ranging from 8 to 32 (Larsen et al., 1979). The scale demonstrates high internal consistency ($\alpha = .92$) and has been extensively validated across diverse service delivery contexts, including digital mental health platforms.

Data Analysis

Quantitative data were analyzed using IBM SPSS Statistics (Version 27) and R statistical software (Version 4.3). Descriptive statistics—including means, standard deviations, frequencies, and percentages—were computed for all demographic variables, engagement metrics, and outcome measure scores. Data normality was assessed using the Shapiro-Wilk test and visual inspection of Q-Q plots prior to inferential analysis.

Inferential analyses included: (a) paired-sample t-tests to examine pre–post differences in PHQ-9, GAD-7, WHO-5, and MSPSS scores, with Cohen's d calculated as a measure of effect size; (b) multiple regression analysis to examine whether engagement level predicted follow-up mental health outcomes after controlling for baseline symptom severity; and (c) Pearson correlation analysis to examine associations among usability, satisfaction, and engagement variables. Effect sizes were interpreted according to Cohen's (1988) conventions: d = 0.20 (small), d = 0.50 (medium), d = 0.80 (large).

Qualitative data were analyzed using reflexive thematic analysis following Braun and Clarke's (2006) six-phase framework: (1) data familiarization through repeated engagement with interview transcripts; (2) systematic generation of initial codes from meaningful data segments; (3) identification of recurring patterns and candidate themes; (4) development of a thematic map; (5) review and refinement of themes; and (6) final definition, naming, and reporting. Multiple researchers independently coded a randomly selected 25% of interview transcripts, with inter-rater reliability assessed using Cohen's kappa ($\kappa = .82$, indicating strong agreement) before resolving discrepancies through discussion and consensus.

Validity and Reliability

The validity and reliability of the study were strengthened through multiple procedural and analytical strategies. Quantitative reliability was enhanced through exclusive use of internationally validated instruments with established psychometric properties (Kroenke et al., 2001; Spitzer et al., 2006). Internal consistency of all scales was verified within the current sample, with Cronbach's alpha coefficients exceeding .80 for all instruments. Methodological triangulation, achieved through the convergent integration of quantitative and qualitative findings, enhanced construct validity and provided cross-method corroboration of key findings (Creswell & Plano Clark, 2018; Lincoln & Guba, 1985). Researcher triangulation in qualitative coding reduced the risk of individual interpretive bias. Member checking was employed in qualitative analysis, with key thematic findings shared with a subsample of interview participants to verify the accuracy of interpretations.

Ethical Considerations

The study adhered to internationally recognized ethical principles governing research involving human participants, including those outlined in the World Medical Association's Declaration of Helsinki (2013) and the ethical guidelines for digital mental health research articulated by Luxton et al. (2011).

Informed consent was obtained electronically from all participants prior to enrollment, with consent documentation clearly explaining the study's purpose, procedures, voluntary nature, rights of withdrawal, data handling practices, confidentiality protections, and procedures for escalation to crisis services. All data collected through the platform were anonymized, encrypted using AES-256 standards, and stored on password-protected servers accessible only to authorized researchers. The study complied with Kenya's Data Protection Act (2019) throughout all phases of data collection, storage, and analysis.

The study incorporated specific ethical safeguards relevant to AI-powered mental health systems. Crisis detection and escalation protocols were implemented to ensure that users presenting with indicators of acute psychological distress or suicidal ideation were immediately connected to available human counselors and directed to emergency mental health services. Human mental health professionals maintained active oversight of the platform throughout the intervention period, reviewing flagged conversations and providing timely clinical response as required. The EMNS platform was explicitly framed as a supplementary support tool rather than a substitute for professional mental health care, and this framing was consistently communicated to all users throughout the intervention.

RESULTS AND FINDINGS

Demographic Characteristics of Participants

A total of 150 participants completed both the baseline and follow-up assessments and were included in the quantitative analysis. An additional 12 participants withdrew or were lost to follow-up and were excluded from primary analyses. Demographic characteristics of the analytic sample are presented in Table 1.

Table 1. Demographic Characteristics of Study Participants (N = 150)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	82	54.7
	Female	68	45.3
Occupation	Student	91	60.7
	Employed	43	28.7
	Other / Unemployed	16	10.6
Age Group	18–24 years	79	52.7
	25–34 years	48	32.0
	35 years and above	23	15.3
Education Level	Undergraduate	85	56.7
	Postgraduate	31	20.7
	Secondary / Other	34	22.6
Primary Device	Smartphone	112	74.7
	Laptop / Desktop	38	25.3

The sample was predominantly composed of students (60.7%) and young adults aged 18–24 years (52.7%), consistent with the digital mental health platform's target population. Smartphones were the primary device used to access EMNS (74.7%), underscoring the importance of mobile-optimized platform design in this context.

Baseline Mental Health Characteristics

At baseline, participants demonstrated clinically meaningful levels of depression and anxiety symptoms. The mean PHQ-9 score of 14.2 (SD = 4.8) fell within the moderate depression severity range (10–14), while the mean GAD-7 score of 13.1 (SD = 4.2) indicated moderate anxiety (10–14). The mean WHO-5 score of 42.5 (SD = 14.6) was below the established threshold of 50, indicating impaired well-being across the sample. These baseline characteristics confirm that the study enrolled a clinically appropriate population with genuine mental health support needs.

Mental Health Outcomes: Pre–Post Comparisons

Table 2 presents the pre–post mental health outcomes, including paired t-test results and effect sizes. Statistically significant improvements were observed across all four primary outcome measures following the three-month EMNS intervention.

Table 2. Pre–Post Mental Health Outcome Comparisons (N = 150)

Instrument	Baseline Mean (SD)	Follow-up Mean (SD)	Mean Change	t-statistic	p-value	Cohen's d
PHQ-9	14.2 (4.8)	8.7 (4.1)	−5.5	$t(149) = 13.76$	$< .001$	1.12
GAD-7	13.1 (4.2)	7.9 (3.8)	−5.2	$t(149) = 12.94$	$< .001$	1.08
WHO-5	42.5 (14.6)	67.4 (13.2)	+24.9	$t(149) = -19.43$	$< .001$	1.43
MSPSS	52.1 (11.4)	60.4 (10.8)	+8.3	$t(149) = -8.87$	$< .001$	0.92

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PHQ-9 depression scores decreased significantly from a mean of 14.2 (SD = 4.8) at baseline to 8.7 (SD = 4.1) at follow-up, representing a mean reduction of 5.5 points ($t(149) = 13.76$, $p < .001$, $d = 1.12$). According to Cohen's (1988) conventions, this represents a large effect size, indicating clinically meaningful improvement. The proportion of participants in the moderate-to-severe depression range (PHQ-9 $\geq$ 10) decreased from 68.0% at baseline to 32.7% at follow-up.

GAD-7 anxiety scores reduced significantly from 13.1 (SD = 4.2) at baseline to 7.9 (SD = 3.8) at follow-up (mean reduction = 5.2 points; $t(149) = 12.94$, $p < .001$, $d = 1.08$), again representing a large effect size. The proportion of participants with moderate-to-severe anxiety (GAD-7 $\geq$ 10) decreased from 72.0% at baseline to 34.0% at follow-up.

WHO-5 well-being scores improved substantially from a baseline mean of 42.5 (SD = 14.6) to a follow-up mean of 67.4 (SD = 13.2), a mean increase of 24.9 points ($t(149) = -19.43$, $p < .001$, $d = 1.43$). This very large effect size indicates that EMNS engagement was associated with a clinically significant shift from impaired to adequate psychological well-being across most participants.

MSPSS perceived social support scores increased from a mean of 52.1 (SD = 11.4) at baseline to 60.4 (SD = 10.8) at follow-up (mean increase = 8.3 points; $t(149) = -8.87$, $p < .001$, $d = 0.92$), representing a large effect size and indicating meaningful improvement in users' sense of social connectedness and support.

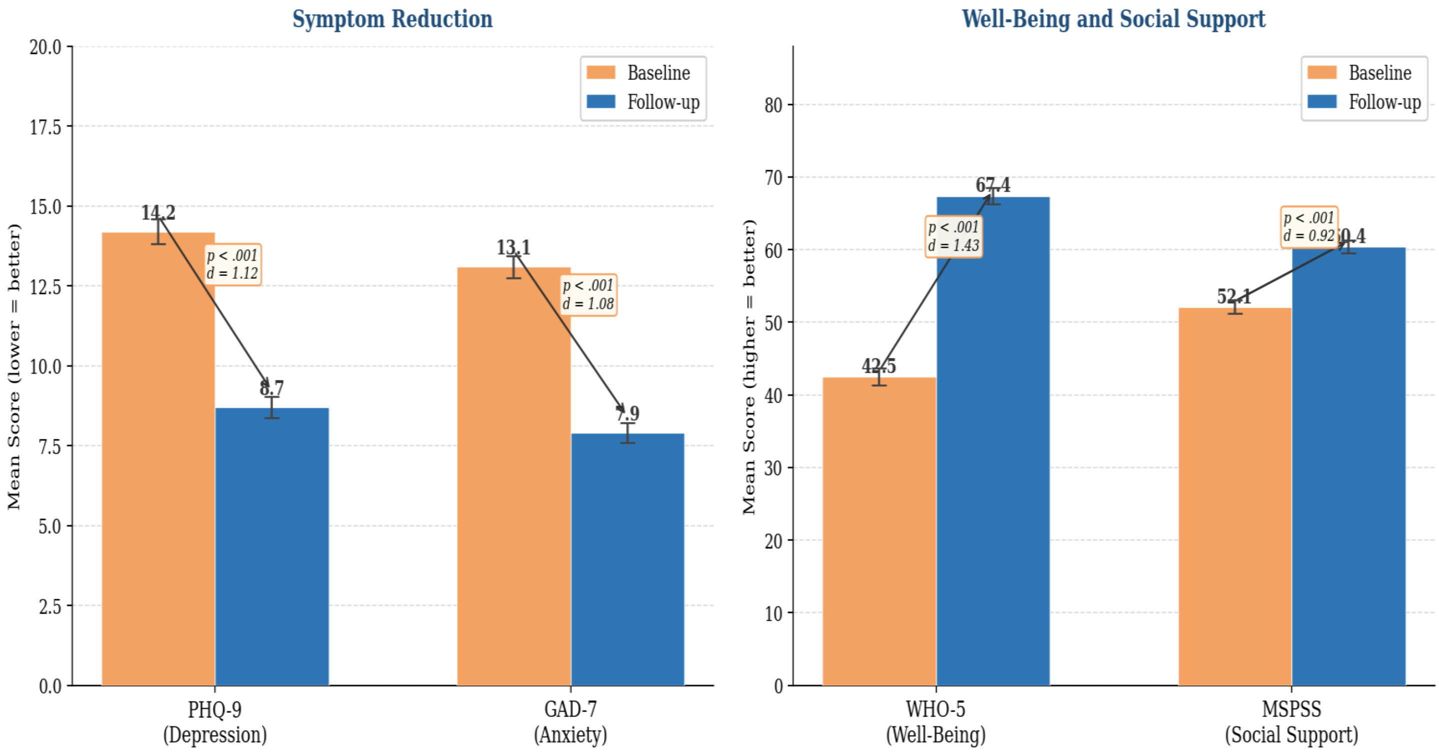

Figure 3. Pre-Post Mental Health Outcome Comparisons (N = 150)

Figure 5. Pre–post comparison of mean scores on primary mental health outcome measures (PHQ-9, GAD-7, WHO-5, MSPSS). All comparisons statistically significant at p < .001. Error bars represent standard errors of the mean. Effect sizes (Cohen's d) annotation

Platform Usability and User Satisfaction

System usability was assessed using the SUS, yielding a mean score of 79.4 (SD = 11.2). This score falls within the "good" usability range according to established SUS benchmarks (Bangor et al., 2008), exceeding the industry standard threshold of 68 and approaching the "excellent" threshold of 85. Client satisfaction, measured by the CSQ-8, yielded a mean score of 27.1 out of 32 (SD = 3.4), indicating high overall satisfaction with EMNS services. Table 3 presents usability and satisfaction outcomes alongside comparative benchmarks.

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Table 3. Platform Usability (SUS) and Satisfaction (CSQ-8) Outcomes

Measure	Study Mean (SD)	Benchmark / Maximum	Interpretation
SUS	79.4 (11.2)	68 = Above Average; 85 = Excellent	Good Usability
CSQ-8	27.1 (3.4)	Maximum = 32	High Satisfaction

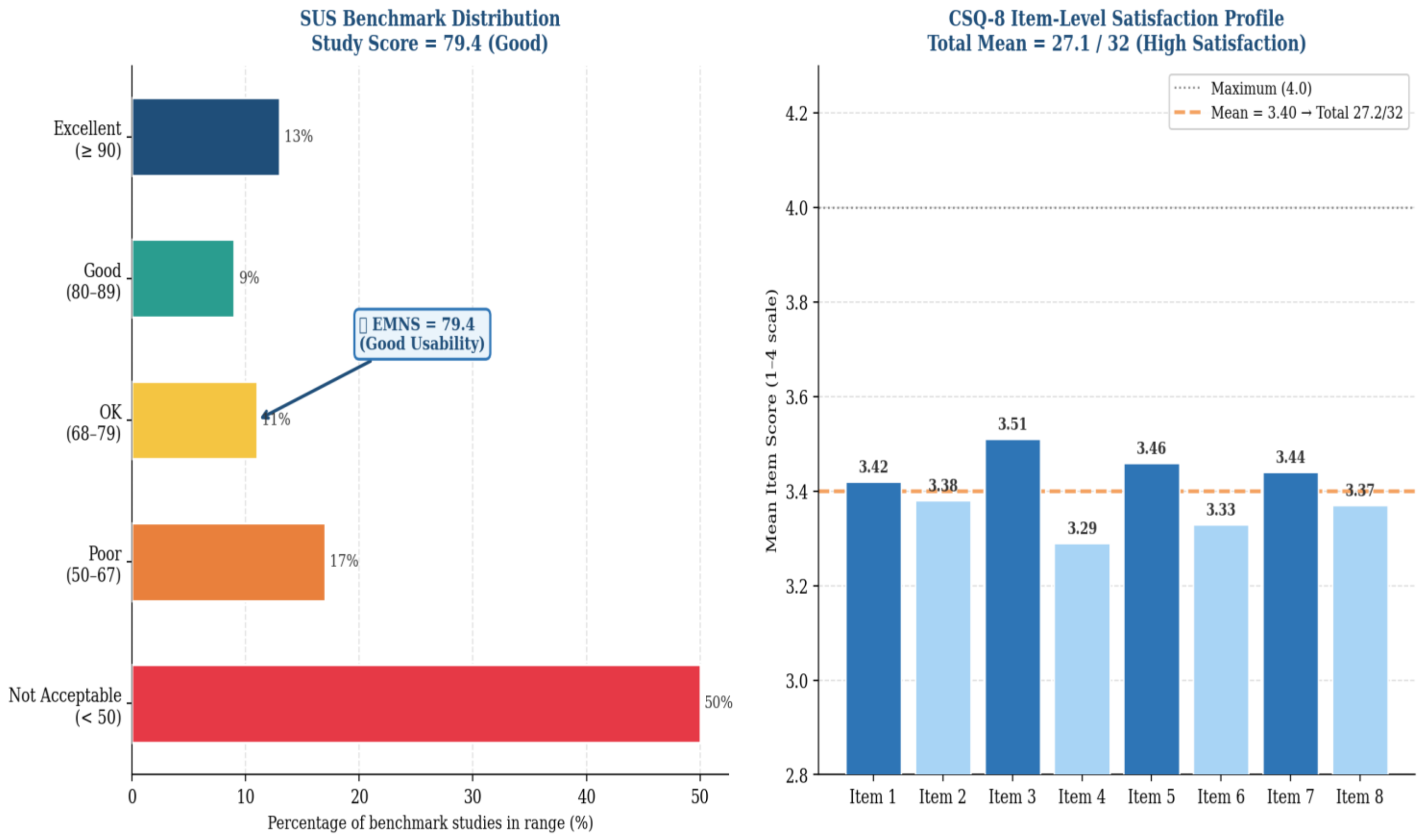

Figure 6. User evaluation of EMNS: (Left) SUS benchmark distribution showing EMNS score of 79.4 in the “Good” usability range. (Right) CSQ-8 item-level satisfaction profile showing all items above 3.29 on a 4-point scale.

Engagement Metrics

Platform engagement data collected through automated system monitoring across the three-month intervention period revealed consistent and sustained usage patterns. Table 4 presents the mean engagement statistics per user over the study period.

Table 4. EMNS Platform Engagement Statistics (N = 150, Three-Month Period)

Platform Feature	Mean Usage per User	SD	Range
Elevana AI Chatbot Sessions	24.3 sessions	8.7	4–56
Human Counseling Sessions	5.2 sessions	2.4	0–12
Peer Support Community Visits	11.4 visits	5.8	0–34
Psychoeducational Resource Downloads	18.1 resources	7.2	2–48

Platform Feature	Mean Usage per User	SD	Range
Average Session Duration (minutes)	22.4 min	9.1	5–68
Platform Login Frequency (per week)	4.8 logins	2.1	1–14

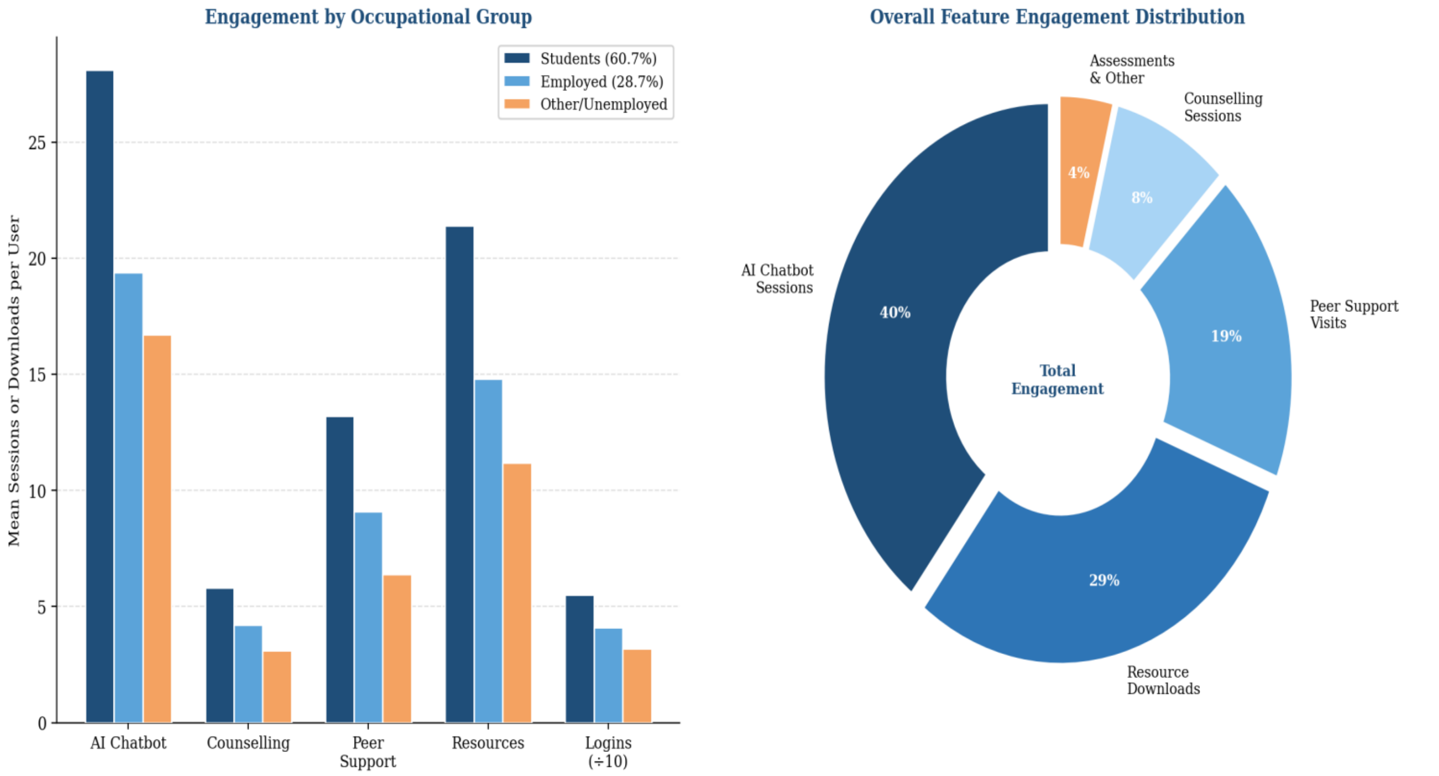

Figure 7. Distribution of user engagement across EMNS platform features. Left: engagement by occupational group (students, employed, other). Right: overall proportional feature engagement expressed as a donut chart.

The engagement data indicate that users interacted with EMNS consistently across the intervention period, with a mean of 24.3 Elevana AI chatbot sessions per user—approximately two sessions per week. Sustained engagement across multiple platform features suggests that the hybrid structure of EMNS, offering diverse modalities of support, contributed to continued user involvement beyond initial interaction.

Regression Analysis: Engagement as a Predictor of Outcomes

Multiple regression analysis was conducted to examine whether platform engagement level predicted follow-up mental health outcomes after controlling for baseline symptom severity. Higher overall engagement (operationalized as the composite of AI session frequency, counseling session attendance, and peer support participation) significantly predicted lower PHQ-9 scores at follow-up ($\beta = -0.31$, $p < .001$), lower GAD-7 scores ($\beta = -0.28$, $p < .001$), higher WHO-5 scores ($\beta = 0.34$, $p < .001$), and higher MSPSS scores ($\beta = 0.22$, $p = .006$), after controlling for baseline scores. These findings suggest a dose-response relationship between EMNS engagement and mental health outcomes, consistent with engagement literature in digital mental health (Perski et al., 2017).

Qualitative Findings

Thematic analysis of the 25 participant and five counselor interviews generated five overarching themes, each comprising multiple subthemes. These themes are described below with illustrative participant quotations.

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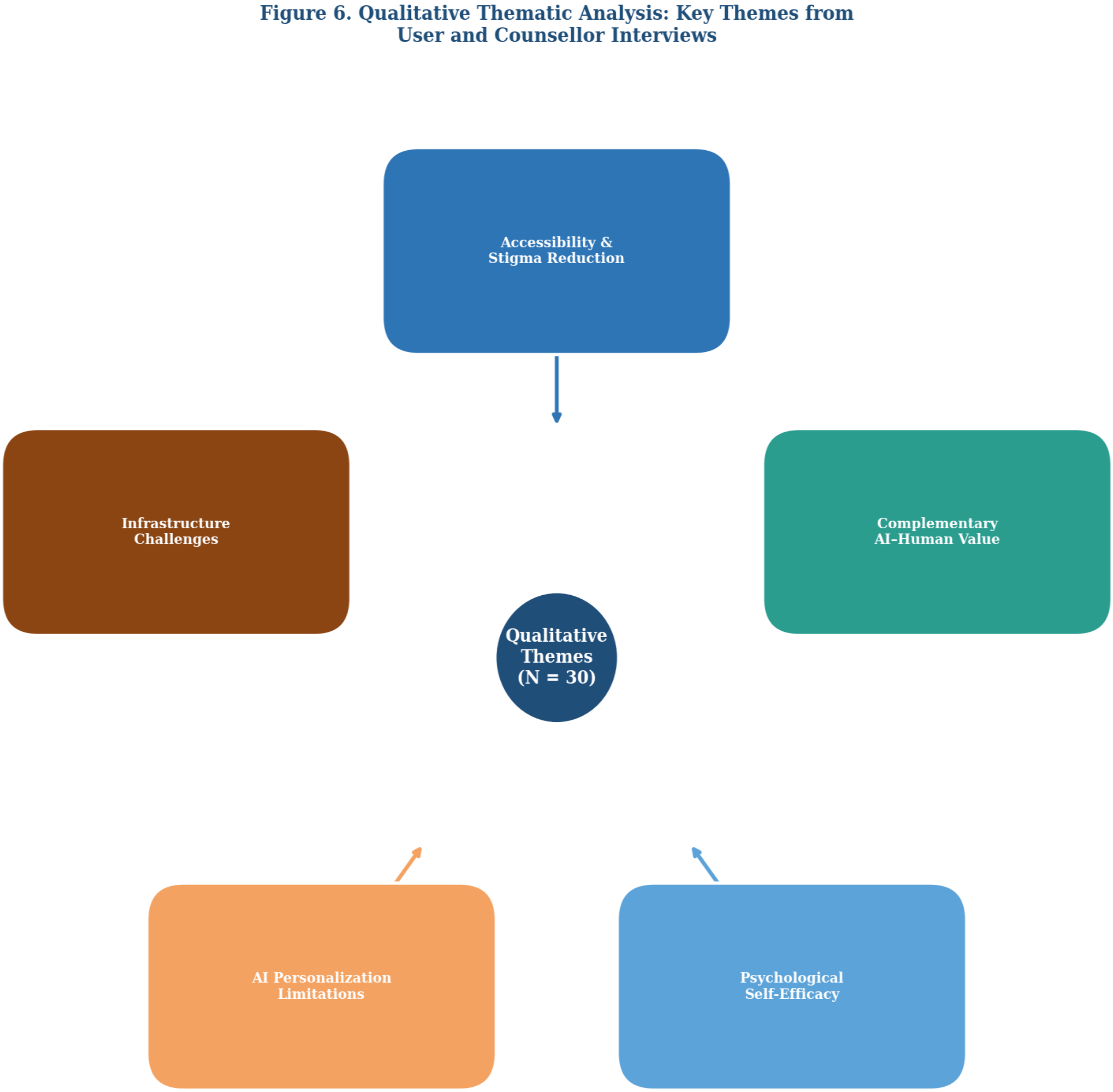

Figure 8. Qualitative thematic analysis wheel illustrating five key themes emerging from semi-structured interviews with EMNS users (n = 25) and mental health counsellors (n = 5).

Theme 1: Accessibility and Removal of Barriers to Help-Seeking

Participants consistently identified EMNS's continuous availability as its most transformative feature. The ability to access support at any time—including late at night, during work breaks, or from rural locations—was described as removing barriers that had previously precluded help-seeking. Participants reported that the anonymity of the digital environment significantly reduced stigma-related inhibitions, enabling more candid disclosure than they would have felt comfortable making in face-to-face settings. Students, in particular, noted that the platform's accessibility enabled them to seek support during academic stress periods without disrupting their schedules.

Theme 2: Complementary Value of AI and Human Support

A consistent theme across interviews was the perceived complementarity of AI-driven and human-delivered support components. Participants described Elevana AI as providing reliable, responsive, non-judgmental initial support that was particularly valuable for routine emotional check-ins, coping strategy guidance, and psychoeducational content. However, participants uniformly emphasized that human counselors provided an irreplaceable dimension of empathy, contextual understanding, and professional guidance, particularly for more complex or persistent psychological concerns. This theme directly supports the hybrid model rationale and suggests that neither component alone would have achieved the observed outcomes.

Theme 3: Enhanced Psychological Self-Efficacy and Empowerment

Many participants reported that engagement with EMNS, particularly through the psychoeducational resource library and structured AI intervention modules, enhanced their understanding of their own mental health and increased their confidence in managing psychological challenges. This perceived increase in mental health literacy and self-efficacy was described as extending beyond the platform to influence help-seeking behavior in other contexts, including family support and peer relationships.

Theme 4: Limitations of Conversational AI in Complex Emotional Contexts

Despite the generally positive reception of Elevana AI, participants identified notable limitations in the chatbot's responsiveness to complex emotional presentations. Some users reported that AI responses occasionally felt formulaic, repetitive, or insufficiently attuned to the specific nuances of their distress. These findings are consistent with broader literature on the limitations of current NLP systems in capturing emotional complexity (Luxton et al., 2011) and reinforce the clinical necessity of human oversight within hybrid digital mental health models.

Theme 5: Infrastructure and Technical Challenges

Several participants, particularly those in peri-urban and rural locations, reported intermittent challenges associated with internet connectivity, data costs, and device compatibility. These infrastructure-level barriers represent important equity considerations for the scalability of EMNS beyond digitally privileged populations and directly inform future development priorities, including offline functionality and data-light interaction modes.

DISCUSSION

Overview of Key Findings

This study presented the design, implementation, and preliminary evaluation of the Elevate Minds Network System (EMNS), a hybrid digital mental health platform integrating Elevana AI, virtual human counseling, peer support, and psychoeducational resources. The findings collectively suggest that EMNS is a feasible, acceptable, and potentially effective model for improving mental health service delivery among digitally connected adults, with significant implications for addressing the mental health treatment gap in LMIC contexts.

The most theoretically significant finding is the large-to-very-large effect sizes observed across all four primary mental health outcome measures. PHQ-9 and GAD-7 reductions of 5.5 and 5.2 points respectively, with effect sizes exceeding $d = 1.0$, are substantially larger than those typically reported in meta-analyses of digital mental health interventions (mean $d \approx 0.56$, Linardon et al., 2020). While this study's pre–post design without a control group precludes attribution of these changes to EMNS specifically, the magnitude of observed change provides a strong signal of potential efficacy warranting examination in controlled trials.

Accessibility and Stigma Reduction

The accessibility of EMNS emerged as its most consistently valued attribute across both quantitative engagement data and qualitative interview narratives. The platform's 24/7 availability, digital anonymity, and multi-device

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accessibility directly addressed several of the most entrenched barriers to mental health help-seeking in the Kenyan context—including stigma, professional availability constraints, and geographic inaccessibility. These findings align with a substantial body of digital mental health research demonstrating that online platforms reduce psychological barriers to help-seeking, particularly among populations who perceive strong stigma associated with formal mental health care (Rickwood et al., 2005; Clement et al., 2015).

The stigma reduction effect of EMNS is particularly significant within the Kenyan cultural context, where mental health conditions remain associated with spiritual explanations and social shame in many communities (Ae-Ngibise et al., 2010). The anonymous, private, and non-judgmental nature of digital interaction may create a psychological safe space in which individuals feel able to disclose and explore mental health concerns that they would be reluctant to raise with family members, community peers, or even professional clinicians in face-to-face contexts.

The Hybrid Model: Evidence for Complementary AI-Human Care

The complementary relationship between AI-mediated and human-delivered support components identified through qualitative analysis is one of the study's most clinically meaningful findings. Participants' descriptions of Elevana AI as a reliable first-line support mechanism that facilitates initial help-seeking and provides between-session support, while human counselors contribute indispensable empathy and clinical expertise for complex presentations, directly instantiate the theoretical framework proposed by Mohr et al. (2013) and empirically supported by Lim et al.'s (2022) meta-analysis.

This finding has important implications for the design of future digital mental health systems. The evidence from EMNS suggests that AI should not be conceptualized as a replacement for human mental health professionals but rather as a complementary infrastructure that extends the reach and accessibility of human-delivered care. Artificial intelligence can effectively handle the routine, scalable aspects of mental health support—psychoeducation delivery, emotional check-ins, coping strategy guidance, and monitoring—while human professionals focus their clinical expertise on complex assessment, therapeutic relationship development, and crisis management. This division of labor represents an ethically sound and resource-efficient model for extending mental health service coverage in settings where professional workforce capacity is severely constrained.

Engagement, Dose-Response, and Sustained Utilization

The sustained engagement patterns observed throughout the three-month intervention period are noteworthy, given that engagement and retention represent chronic challenges in digital mental health research (Baumeister et al., 2014; Perski et al., 2017). The mean of 24.3 AI chatbot sessions per user over three months suggests habitual, routine engagement rather than sporadic usage, and the regression finding of a significant positive association between engagement and outcome improvement is consistent with the dose-response patterns documented in digital mental health literature (Perski et al., 2017). These patterns likely reflect the multi-component hybrid structure of EMNS, which offers diverse, complementary forms of support and thereby reduces the risk of user disengagement due to feature repetitiveness or limited modality.

Implications for Healthcare Systems and Policy

The findings of this study carry several important implications for healthcare systems, universities, governments, and mental health organizations operating in LMIC contexts.

For universities and higher education institutions: The significant proportion of student participants in this study and their disproportionately high baseline mental health burden underscore the urgent need for accessible, scalable digital mental health infrastructure within university settings. Institutions should consider integrating hybrid digital mental health platforms into their student welfare ecosystems as a complement to—rather than replacement for—traditional counseling services. The EMNS model, developed within a Kenyan university context, provides a contextually grounded proof of concept for such integration.

For national healthcare systems: Governments and national health authorities in LMICs should consider hybrid digital mental health platforms as a viable strategy for extending mental health service coverage without proportional increases in professional workforce requirements. The EMNS findings suggest that AI-augmented hybrid systems can achieve clinically meaningful outcomes while remaining accessible through widely available smartphones—a critical consideration in resource-constrained environments with high mobile penetration.

For international mental health organizations: The WHO's Mental Health Action Plan 2013–2030 and the Sustainable Development Goals' commitment to universal health coverage both prioritize the expansion of mental health service access in LMICs. Hybrid digital mental health platforms such as EMNS represent scalable, evidence-informed mechanisms through which these policy commitments can be advanced. International organizations should prioritize funding, capacity building, and knowledge-sharing to support the development and validation of contextually appropriate digital mental health systems in underserved regions.

For AI and health technology developers: The finding that AI chatbot limitations—particularly in emotional nuance and contextual responsiveness—constitute a significant user concern highlights critical priorities for next-generation conversational AI development in mental health applications. Advances in cultural and linguistic adaptation, personalization through federated learning, and enhanced crisis detection sensitivity are essential to the responsible scaling of AI mental health tools.

Data Governance, Privacy, and Ethical AI

The ethical governance of AI-powered mental health systems warrants sustained scholarly and policy attention beyond the findings of individual empirical studies. The integration of AI in mental health care introduces specific risks that require proactive governance: algorithmic bias may differentially disadvantage users from minority demographic groups; data privacy vulnerabilities may expose sensitive mental health information to unauthorized disclosure; and over-reliance on AI responses may delay appropriate crisis intervention for individuals with acute psychological distress. The EMNS study addressed these concerns through encryption, crisis escalation protocols, professional oversight, and transparent informed consent procedures, but the broader field requires the development of regulatory frameworks and professional standards specific to AI in mental health (Jobin et al., 2019; Char et al., 2018).

Scalability and Implementation Framework

The scalability of EMNS is predicated on several enabling conditions that must be systematically addressed for successful wider deployment. Technical scalability requires robust cloud infrastructure capable of supporting concurrent users, secure data storage at scale, and reliable performance across diverse device types and connectivity contexts. The finding that some participants experienced challenges with internet connectivity and data costs highlights the importance of developing data-light interaction modes and offline functionality for users in low-connectivity environments.

A phased implementation framework is recommended for EMNS scaling: Phase 1 should focus on pilot refinement within specific institutional contexts (such as universities or workplace wellness programs), incorporating ongoing user feedback and clinical review. Phase 2 should involve adaptation for specific cultural and linguistic contexts, including Swahili language interface development and culturally informed content curation. Phase 3 should encompass integration with national health information systems and formal primary healthcare referral pathways, enabling EMNS to function as a recognized component of the continuum of mental health care rather than as an isolated digital tool. Each phase should incorporate rigorous evaluation, including the randomized controlled trials necessary to establish definitive causal evidence of clinical effectiveness.

Risk Management and AI Limitations

Responsible deployment of AI in mental health contexts requires systematic attention to risk management at both the individual user level and the system level. At the individual level, the most significant risk is inadequate crisis response: AI systems that fail to reliably detect acute psychological distress, suicidal ideation, or immediate safety concerns may inadvertently delay life-saving intervention. The EMNS platform's crisis detection and escalation protocols, while functional, require continuous refinement through regular clinical review of flagged interactions and ongoing algorithm improvement.

At the system level, risks include algorithmic bias, data security breaches, platform downtime affecting users during moments of acute need, and unintended therapeutic harm through misleading or contextually inappropriate AI responses. Governance mechanisms to mitigate these risks should include regular bias auditing, penetration testing and security reviews, clearly documented procedures for platform unavailability, and transparent communication to users about the limitations of automated systems. The principle of "human in the loop"—whereby human professionals maintain meaningful oversight of AI-mediated interactions rather than ceding clinical responsibility to automated systems—should be treated as a non-negotiable design requirement for AI mental health applications operating with vulnerable populations.

Study Limitations

Several limitations should be considered when interpreting the findings of this study. First, and most significantly, the study adopted a single-group pre–post observational design without randomization or a control condition. While the observed changes in mental health outcomes were statistically significant and clinically meaningful in magnitude, the absence of a control group makes it impossible to determine whether these changes were specifically attributable to EMNS engagement or to non-specific factors such as spontaneous symptom remission, regression to the mean, or concurrent help-seeking. A randomized controlled trial comparing EMNS to a waitlist control or active comparison condition is necessary to establish causal evidence of effectiveness.

Second, the study relied exclusively on self-reported assessment instruments, which are subject to recall bias, social desirability effects, and subjective interpretation. Although all instruments used have established psychometric properties, their self-report nature introduces measurement uncertainty that objective clinical assessments or structured diagnostic interviews would reduce.

Third, purposive sampling and the exclusive recruitment of digitally engaged users limits the generalizability of findings to populations with limited internet access, lower digital literacy, or reduced familiarity with online mental health systems. The significant digital divide that persists in many LMICs means that the populations with the greatest mental health burden and the fewest existing resources may be precisely those least likely to access digital mental health interventions as currently designed.

Fourth, the three-month intervention period, while sufficient for preliminary evaluation, is insufficient to assess the sustainability of mental health improvements over time, the long-term trajectory of platform engagement, or the durability of therapeutic gains following disengagement from the platform. Longitudinal follow-up studies are required to address these questions.

Finally, although the study sample was diverse across occupational and age categories, the predominance of university students and individuals with secondary or tertiary educational qualifications may limit the applicability of findings to less educated populations who represent a significant proportion of those experiencing mental health burden in low-resource settings.

CONCLUSION AND RECOMMENDATION

This study presented the design, implementation, and preliminary evaluation of the Elevate Minds Network System (EMNS), a hybrid digital mental health platform integrating AI-powered conversational support, virtual human counseling, peer interaction, and psychoeducational resources. The findings demonstrate that EMNS is technically feasible, user-acceptable, and associated with statistically significant and clinically meaningful improvements in depression symptoms, anxiety levels, psychological well-being, and perceived social support over a three-month pilot period. High usability and satisfaction scores, sustained engagement patterns, and rich qualitative evidence of stigma reduction and user empowerment collectively position EMNS as a promising model for addressing critical gaps in mental health service delivery.

The evidence generated by this study makes a meaningful contribution to the nascent but rapidly growing literature on hybrid AI-human digital mental health systems, particularly in the underrepresented LMIC and sub-

Saharan African contexts. It provides empirical grounding for the theoretical proposition that AI should function as a complementary and augmentative element of human-delivered mental health care rather than as an autonomous replacement for professional clinical services.

Based on the findings and limitations of this study, the following recommendations are proposed:

1. Future research should prioritize randomized controlled trials to establish causal evidence of EMNS effectiveness and to compare the hybrid model against active comparison conditions, including standalone AI programs and standard teletherapy services.
2. EMNS developers should invest in advanced NLP capabilities to address identified limitations in AI emotional nuance and contextual responsiveness, including culturally adapted language models trained on diverse African linguistic and cultural datasets.
3. Platform scalability should be advanced through offline functionality development, data compression, and Swahili language interface localization to ensure equitable access for users in low-connectivity environments.
4. National health authorities and university administrations should explore the integration of platforms such as EMNS into formal mental health care pathways, establishing clear referral protocols, professional oversight requirements, and data governance standards.
5. Ethical AI governance frameworks specific to mental health applications should be developed and adopted by DMHI developers, drawing on established principles of beneficence, non-maleficence, autonomy, justice, and explicability.
6. Longitudinal studies with extended follow-up periods of 12 months or more are required to assess the sustainability of mental health improvements and long-term retention patterns in hybrid digital mental health systems.
7. Future implementations should explore integration with primary healthcare systems and community-level mental health workers to extend EMNS's reach to populations with limited digital connectivity but significant mental health support needs.

In conclusion, EMNS represents a meaningful and timely contribution to the field of accessible, scalable, and ethically governed mental health service delivery. With continued development, rigorous evaluation, and appropriate institutional support, it has the potential to contribute substantially to reducing the global mental health treatment gap, particularly in underserved populations where the burden of mental illness is greatest and existing resources are most limited.

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Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
BIT	Behavioral Intervention Technology
CBT	Cognitive Behavioral Therapy
CSQ-8	Client Satisfaction Questionnaire-8
DALY	Disability-Adjusted Life Year
DMHIs	Digital Mental Health Interventions
EMNS	Elevate Minds Network System
GAD-7	Generalized Anxiety Disorder-7
GDPR	General Data Protection Regulation
LMIC	Low- and Middle-Income Country
ML	Machine Learning
MSPSS	Multidimensional Scale of Perceived Social Support
NLP	Natural Language Processing
PHQ-9	Patient Health Questionnaire-9
RIO	Research, Innovation and Outreach
SPSS	Statistical Package for the Social Sciences
SUS	System Usability Scale
TAM	Technology Acceptance Model
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
WHO	World Health Organization
WHO-5	WHO-5 Well-Being Index
WMA	World Medical Association
YLD	Years Lived with Disability

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