

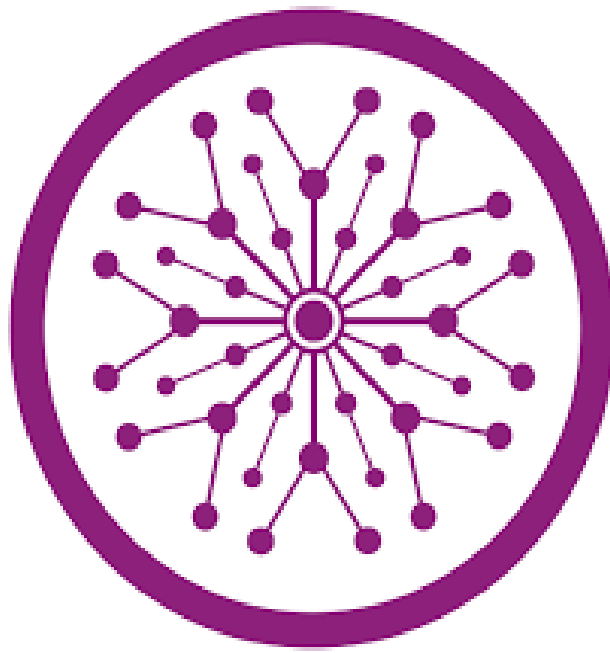
AI-Powered Maternal Mental Health Monitoring System for Low-Literacy Users in Pakistan

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Chapter 1

INTRODUCTION

Maternal mental health disorders represent a critical global public health challenge. According to the World Health Organization, approximately 10 percent of pregnant women and 13 percent of women in the postpartum period experience mental health disorders, primarily depression and anxiety [2]. In low- and middle-income countries, these rates are significantly higher, with 16 percent affected during pregnancy and 20 percent after childbirth [1]. In Pakistan, the situation is particularly severe, with postpartum depression prevalence rates ranging from 28 to 63 percent [10], placing it among the highest in South Asia. A comprehensive 2024 systematic review analyzing 61 studies with 23,838 women found pooled prevalence rates of 37 percent for antenatal depression and varying rates of postnatal depression [4]. These alarming statistics underscore an urgent need for accessible mental health screening and support systems tailored to the Pakistani context, especially for women in underserved communities with limited literacy and healthcare access.

The consequences of untreated maternal mental health disorders extend beyond individual suffering, significantly impacting fetal development, child health outcomes, and family wellbeing [55, 56]. Despite this critical need, multiple barriers prevent Pakistani women from accessing mental health services, including cultural stigma surrounding mental illness [5], limited healthcare infrastructure, shortage of mental health professionals [59], low literacy rates, and language barriers [60]. Current digital health interventions predominantly target English-speaking, high-literacy populations and lack cultural adaptation for low-resource settings where the need is greatest [38, 39].

Artificial intelligence has emerged as a promising solution for expanding mental health care access, with recent studies demonstrating that AI-based systems can effectively support mental health screening and monitoring [32, 26]. Advanced large language models have shown potential in providing mental health support through conversational interfaces [29, 27]. However, these technologies remain largely inaccessible to low-literacy populations who face the highest maternal mental health burden [37]. This research addresses this critical gap by developing an AI-powered maternal mental health monitoring system that utilizes voice-

based interfaces, Roman Urdu support [42], and culturally appropriate design to democratize mental healthcare access for underserved Pakistani mothers with limited literacy levels.

1.1 Background and Motivation

Maternal mental health encompasses the psychological and emotional wellbeing of women during pregnancy, childbirth, and the postpartum period [1]. This critical phase represents a vulnerable period for psychiatric disorders, with depression, anxiety, and stress being the most prevalent conditions [53]. The perinatal period is characterized by significant physiological, hormonal, and psychosocial changes that can trigger or exacerbate mental health conditions, particularly among women facing socioeconomic challenges [54].

Pakistan faces a particularly severe maternal mental health crisis. Studies conducted across various provinces reveal consistently high prevalence rates of perinatal depression and anxiety disorders [4, 6]. Recent research in 2024 found that mothers with postnatal anxiety in Pakistan face unique cultural and social challenges [6]. Risk factors significantly associated with maternal mental health disorders in Pakistan include low socioeconomic status, illiteracy, unemployment, marital problems, insufficient antenatal care, previous psychiatric illness, and lack of family support [9, 5]. Figure 1.1 illustrates the major risk factors contributing to maternal mental health disorders.

The impact of maternal mental health disorders extends to multiple domains. Maternal stress, anxiety, and depression during pregnancy are associated with intrauterine growth restriction, preterm birth, low birth weight, and adverse neurodevelopmental outcomes [55]. Studies demonstrate that fetuses of mothers with persistent depression exhibit neurodevelopmental delays at significantly higher rates compared to infants born to non-depressed mothers [57]. Maternal psychological distress affects fetal development through multiple pathways, including dysregulation of the maternal-fetal hypothalamic-pituitary-adrenal axis, altered cortisol exposure, disrupted placental function, and changes in uterine blood flow [56, 58].

Despite the magnitude of this public health challenge, maternal mental health remains significantly underdiagnosed and undertreated in Pakistan [59, 8]. Multiple barriers contribute to this gap, including limited mental health infrastructure, shortage of trained professionals, cultural stigma surrounding mental illness, lack of awareness, and financial constraints [61, 5].

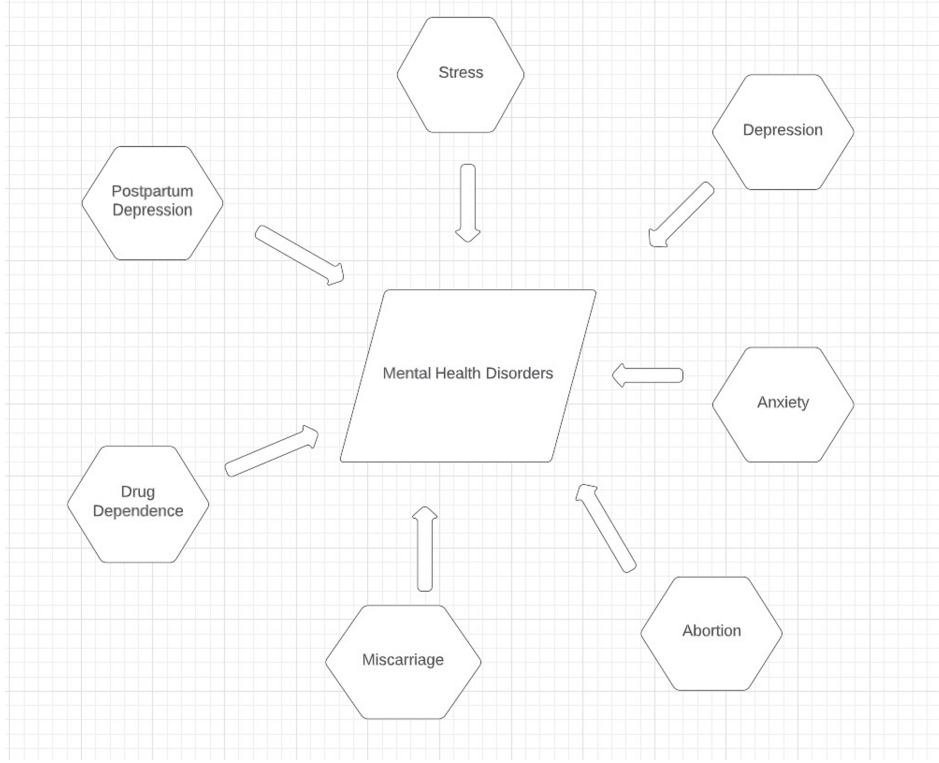


Figure 1.1: Risk factors contributing to maternal mental health disorders including postpartum depression, stress, depression, anxiety, drug dependence, miscarriage, and abortion.

1.1.1 The Role of Digital Health and Artificial Intelligence

Digital health technologies have emerged as potential solutions to expand mental health care access, particularly in resource-limited settings [7]. AI-based conversational agents have demonstrated effectiveness in mental health interventions, with systematic reviews revealing significant reductions in symptoms of depression and psychological distress [32]. Recent 2025 research on AI chatbots for mental health has provided insights into both the values and potential harms from lived experiences of depression [26], while other studies explore the broader AI-enhanced mental health ecosystem [27]. Large language model chatbots have shown promise in providing mental health support [29], and evaluations by mental health professionals indicate potential for cognitive restructuring interventions [30].

However, digital health literacy remains unevenly distributed, with vulnerable populations including individuals with low education levels and limited literacy skills experiencing significantly lower digital health literacy [38, 39]. Recent 2024 research emphasizes the need for system-wide approaches to digital equity, particularly through digital navigation programs for underserved populations [37]. The need for multilingual information in simple language and multimedia materials such as videos and voice interfaces is critical for ensuring accessibility and user

engagement [34].

Current digital mental health tools predominantly use English language interfaces and assume high literacy levels, creating barriers for the majority of Pakistani women who may have limited English proficiency or formal education [43]. Roman Urdu, which uses the Roman alphabet to write Urdu language, has emerged as a widely used communication medium in Pakistan, particularly in digital contexts and among populations with limited formal Urdu education [42]. Integrating speech-to-text technology further reduces literacy barriers by allowing voice-based interaction without requiring reading or writing skills [35, 34].

This research is motivated by the urgent need to develop culturally appropriate, linguistically accessible AI-powered mental health screening tools specifically designed for low-literacy Pakistani mothers [1]. By combining Roman Urdu localization [42], speech-to-text functionality [36], machine learning-based analysis using validated psychological scales [17, 18], and automated report generation, this project aims to democratize access to maternal mental health screening and early intervention.

1.2 Problem Statement

Maternal mental health disorders, particularly postpartum depression, stress, and anxiety, remain significantly underdiagnosed in Pakistan despite affecting a substantial proportion of mothers [4, 10]. The gap between disease prevalence and diagnosis rates represents a critical failure in maternal healthcare that contributes to preventable suffering, adverse pregnancy outcomes, and long-term developmental consequences for children [9, 55].

Multiple interconnected barriers prevent Pakistani women from accessing maternal mental health services. First, cultural stigma surrounding mental illness discourages help-seeking behavior and open discussion of psychological distress [5, 59]. Second, limited healthcare infrastructure and shortage of mental health professionals create access barriers, particularly in rural and underserved areas [61, 8]. Third, low literacy rates and limited English proficiency prevent many women from accessing existing digital health resources [38, 39]. Fourth, financial constraints and competing priorities for household resources limit ability to seek professional care [9].

Existing digital mental health interventions have demonstrated effectiveness in other populations but remain inaccessible to low-literacy populations in developing countries [32, 37]. Current tools predominantly use English language interfaces, require text-based interaction, and assume high levels of digital literacy and internet access [38]. This creates a paradox where the populations facing the

highest maternal mental health burden have the least access to potentially beneficial digital health technologies [39]. Recent research on AI chatbots for mental health highlights both opportunities and challenges in deploying such technologies [26, 28].

Therefore, there exists an urgent need for culturally appropriate, linguistically accessible, AI-powered maternal mental health screening tools specifically designed for low-literacy Pakistani mothers that leverage speech-to-text technology [34], Roman Urdu localization [42], and validated psychological assessment instruments [17, 18] to enable early detection, timely intervention, and improved maternal and child health outcomes.

1.3 Objectives of the Study

The primary objective of this research is to develop and evaluate an AI-powered web application for maternal mental health screening and monitoring that is accessible to low-literacy Pakistani women through Roman Urdu localization and speech-to-text functionality.

Specific objectives include:

1. To design and implement a responsive web-based platform supporting both Roman Urdu and simple English for maternal mental health assessment and user engagement [42, 43].
2. To integrate speech-to-text functionality using AI-powered speech recognition to enable voice-based journal entries and assessment responses, reducing literacy barriers and improving accessibility [35, 34].
3. To incorporate validated psychological screening instruments including the Edinburgh Postnatal Depression Scale (EPDS) [17] and Patient Health Questionnaire-9 (PHQ-9) [18] for evidence-based assessment aligned with international standards.
4. To develop and train machine learning models for analyzing user-generated text and voice data to predict maternal mental health status, risk levels, and provide personalized recommendations [62, 31].
5. To implement automated report generation that provides easy-to-understand mental health insights and recommendations in Roman Urdu or simple English language [65].
6. To conduct comprehensive usability and user experience evaluation to assess the system’s accessibility, acceptability, and satisfaction among low-literacy Pakistani mothers [40, 37].

7. To validate the accuracy and reliability of the AI-based mental health assessment compared to standard clinical screening methods and establish clinical utility [64, 30].

1.4 Research Questions/Hypotheses

Primary Research Question:

How can AI-based technology improve maternal mental health screening accessibility and engagement for low-literacy Pakistani women?

Secondary Research Questions:

- **RQ1:** What is the effectiveness of Roman Urdu localization in improving user comprehension, engagement, and completion rates of mental health assessments compared to English-only interfaces? [42, 43]
- **RQ2:** How accurately can machine learning models predict maternal mental health status using self-reported journal entries, voice data, and structured assessment responses? [62, 30]
- **RQ3:** What features of AI-powered mental health platforms enhance user trust, perceived usefulness, and sustained engagement among low-literacy populations in Pakistan? [41, 26]
- **RQ4:** To what extent does speech-to-text input functionality increase accessibility, user preference, and assessment completion rates compared to text-only interaction? [35, 34]

Research Hypotheses:

- **H1:** Users interacting with the Roman Urdu interface will demonstrate significantly higher assessment completion rates and comprehension scores compared to users interacting with the English-only interface [42].
- **H2:** The integration of speech-to-text functionality will result in increased user engagement frequency and longer, more detailed journal entries compared to text-only input modes [35].
- **H3:** Machine learning models trained on maternal mental health datasets will achieve clinically acceptable accuracy (75%) in predicting maternal depression risk levels and mental health status [64].

- **H4:** Users receiving AI-generated explanations in simple language and local cultural context will report higher satisfaction, understanding, and trust compared to standard clinical report formats [65, 29].

1.5 Scope and Limitations

1.5.1 Scope

This research encompasses the following elements:

Target Population: Pregnant women and postpartum mothers in Pakistan, with primary focus on low-literacy populations and those with limited English proficiency.

Geographic Focus: Urban and semi-urban areas of Pakistan with internet access.

Platform Type: Responsive web application accessible via smartphones, tablets, and desktop computers.

Core Functionalities:

- Mental health assessment using validated EPDS and PHQ-9 scales
- Text and voice-based journal entries with sentiment and emotional analysis
- Machine learning-based risk prediction and mental health status assessment
- Automated report generation with easy-to-understand explanations
- Roman Urdu and simple English language support
- User interface design optimized for low-literacy populations

Technologies Implemented: Speech-to-text conversion using AI models [35, 34], natural language processing for sentiment and emotional analysis [62], machine learning classification algorithms [63], responsive web development frameworks, and secure cloud-based data storage [70].

Evaluation Metrics: System usability [66], user satisfaction, assessment completion rates, prediction accuracy (precision, recall, F1-score) [64], engagement patterns, and user acceptance [41].

Duration: One academic year for development, implementation, and evaluation.

1.5.2 Limitations

Methodological Limitations:

- Reliance on self-reported data; system does not replace clinical diagnosis or professional mental health assessment [69, 67]
- Cannot provide crisis intervention, emergency mental health services, or psychiatric treatment; designed for screening and monitoring only [68]
- Limited to screening and monitoring functions; does not include therapeutic interventions, counseling, or medical treatment

Sample Limitations:

- Prototype testing conducted with limited sample size of users in urban and semi-urban areas with internet access [40]
- May not fully represent rural populations, those without digital access, or users with severe mental illness
- Generalizability limited to Pakistani context; adaptation and validation required for other cultural and linguistic settings [42, 3]

Technical Limitations:

- Requires stable internet connectivity; no offline functionality in initial version
- Speech-to-text accuracy dependent on audio quality, background noise, and accent variations; may require fine-tuning for regional Urdu dialects [34, 35]
- Roman Urdu translation quality and natural language processing performance limited by availability of annotated datasets and pre-trained models [62]

Data Limitations:

- Limited availability of existing publicly available datasets combining Roman Urdu maternal mental health text with validated clinical labels for model training [63]
- Privacy and ethical constraints limit ability to collect, aggregate, and share sensitive mental health data [70]

Ethical and Clinical Limitations:

- System provides screening, information, and recommendations only; cannot diagnose mental health disorders or prescribe treatment [69]
- Potential for user over-reliance on AI recommendations without seeking professional clinical care [26]

- Data privacy, security, and user confidentiality require ongoing vigilance and compliance with healthcare regulations [70]
- System cannot replace human clinical judgment, professional mental health services, or comprehensive maternal healthcare [53]

1.6 Thesis Organization

This thesis is organized into five chapters:

Chapter 1: Introduction provides background on maternal mental health challenges in Pakistan, motivation for AI-based solutions, the specific research problem, objectives of the study, research questions and testable hypotheses, scope of research, and acknowledgment of limitations.

Chapter 2: Literature Review presents a comprehensive review of existing research on maternal mental health epidemiology, risk factors and consequences of perinatal mental health disorders, validated psychological assessment tools and screening instruments, AI and machine learning applications in mental health care, digital health interventions for low-literacy populations, natural language processing and speech recognition technologies, language accessibility in healthcare applications, and identification of research gaps.

Chapter 3: Methodology describes the research design and approach, system architecture and technical design, data collection methods and sources, machine learning model selection and training procedures, evaluation metrics and validation approaches, user study design and participant recruitment, and ethical considerations.

Chapter 4: Results and Discussion presents comprehensive evaluation findings including system performance metrics, machine learning model accuracy and prediction results, user usability and satisfaction assessment, comparison with existing tools, and discussion of strengths, weaknesses, and findings.

Chapter 5: Conclusion and Future Work summarizes key research findings, discusses contributions to maternal mental health research and practice, identifies limitations, and proposes directions for future research including mobile application development, integration with healthcare systems, expansion to additional languages, and longitudinal impact studies.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

This chapter presents a comprehensive review of existing research relevant to the development of an AI-powered maternal mental health monitoring system for low-literacy users in Pakistan. The review systematically explores maternal mental health epidemiology and global burden, risk factors and consequences of perinatal mental health disorders, validated psychological assessment tools and screening instruments, artificial intelligence and machine learning applications in mental health care, speech recognition and voice-based interfaces, digital health interventions for low-literacy populations, ethical and privacy considerations, and identification of research gaps that justify this work.

The literature review is organized to provide a comprehensive understanding of the theoretical and empirical foundations supporting this research. It begins with an examination of maternal mental health challenges globally and specifically in Pakistan, followed by an analysis of screening tools and assessment instruments. The review then explores technological solutions including artificial intelligence, machine learning, natural language processing, and speech recognition before concluding with an identification of critical research gaps that this study addresses.

2.2 Maternal Mental Health: Global and Pakistani Context

2.2.1 Epidemiology of Perinatal Mental Health Disorders

Perinatal mental health disorders represent a significant global public health challenge affecting mothers during pregnancy and the postpartum period. According to the World Health Organization, approximately 10 percent of pregnant women and 13 percent of postpartum women in high-income countries experience mental health disorders, primarily depression and anxiety [2]. In low- and middle-income countries, these rates are substantially higher, with approximately 16 percent affected during pregnancy and 20 percent after childbirth [1].

Depression and anxiety are the most prevalent perinatal mental health

conditions [53]. A systematic review and meta-analysis examining the predictive validity of screening tools found pooled sensitivity and specificity rates across multiple studies, demonstrating the widespread nature of these conditions [12]. Recent research in 2024 has continued to document high prevalence rates across diverse populations and cultural contexts, emphasizing the need for comprehensive screening programs [11].

Among women with perinatal mental health conditions, approximately 20 percent experience suicidal thoughts or undertake acts of self-harm, highlighting the severity and potential consequences of untreated maternal mental health disorders [2]. The burden extends beyond individual suffering, affecting maternal-infant bonding, child development, family relationships, and long-term health outcomes [53].

2.2.2 Maternal Mental Health in Pakistan

Pakistan faces a particularly severe maternal mental health crisis compared to global averages. A comprehensive 2024 systematic review and meta-analysis examining 61 studies with 23,838 women found pooled prevalence rates of 37 percent for antenatal depression, with postnatal depression rates varying across time: 34.2 percent at three months, 40.9 percent at six months, and 43.1 percent at 12 months postpartum [4]. Other studies have reported even higher rates, with postpartum depression prevalence ranging from 28 to 63 percent across different regions of Pakistan [10].

Recent 2024-2025 research has provided additional insights into specific aspects of maternal mental health in Pakistan. A qualitative phenomenology study explored lived experiences of mothers with postnatal anxiety, revealing unique cultural and social challenges [6]. Research examining barriers to maternal mental health care found that knowledge gaps, negative attitudes, and stigmas surrounding postpartum depression within social support systems significantly impede help-seeking behavior [5].

The Safe Motherhood—Accessible Resilience Training (SM-ART) intervention, evaluated through a randomized controlled trial in 2024, demonstrated the potential for structured interventions to promote mental wellbeing among pregnant women in Pakistan [7]. Additionally, research on integrating maternal depression care at primary private clinics in low-income settings has shown promise for expanding access to mental health services [8].

2.2.3 Risk Factors and Consequences

Multiple interconnected risk factors contribute to the high prevalence of maternal mental health disorders in Pakistan. Socioeconomic factors including low socioeconomic status, poverty, and financial constraints represent significant risk factors [9]. Educational factors, particularly illiteracy and low education levels, increase vulnerability to perinatal mental health conditions [4]. Marital and relationship factors such as marital discord, domestic violence, and lack of partner support contribute substantially to risk [5]. Healthcare access factors including insufficient antenatal care, limited access to mental health services, and shortage of trained professionals create barriers to prevention and treatment [8].

The consequences of untreated maternal mental health disorders extend across multiple domains. Maternal consequences include impaired functioning, decreased quality of life, increased risk of suicide and self-harm, and long-term mental health complications [2]. Fetal and neonatal consequences encompass intrauterine growth restriction, preterm birth, low birth weight, and adverse neurodevelopmental outcomes [55, 56]. Child development consequences affect cognitive development, emotional regulation, behavioral problems, and attachment difficulties [57]. Family and social consequences include disrupted family dynamics, impaired maternal-infant bonding, and economic burden on families and healthcare systems [53].

2.2.4 Barriers to Mental Health Care in Pakistan

Multiple barriers prevent Pakistani women from accessing maternal mental health services. Cultural barriers include stigma surrounding mental illness, cultural beliefs attributing mental health issues to spiritual or supernatural causes, and shame associated with seeking psychological help [5, 59]. Structural barriers encompass limited healthcare infrastructure, shortage of mental health professionals (fewer than 0.5 psychiatrists per 100,000 population), geographic barriers in rural areas, and financial constraints [61]. Individual barriers involve lack of awareness about mental health conditions, low mental health literacy, limited education and literacy, and language barriers preventing access to information [60]. Systemic barriers include lack of integration of mental health services into primary healthcare, limited screening and early detection programs, and inadequate training of healthcare providers in perinatal mental health [8].

2.3 Mental Health Screening and Assessment Tools

2.3.1 *Edinburgh Postnatal Depression Scale (EPDS)*

The Edinburgh Postnatal Depression Scale remains the most widely used postpartum depression screening tool globally, having been validated worldwide and translated into numerous languages since its original development in 1987 [17]. The EPDS is a 10-item self-report questionnaire designed specifically to assess postpartum depression, with each item scored from 0 to 3, yielding a maximum score of 30 [11].

Recent systematic reviews and meta-analyses have confirmed the continued validity and reliability of the EPDS across diverse populations. A 2023 meta-analysis examining 17 studies with 1,831 pregnant women found pooled sensitivity of 0.81 and specificity of 0.87 for antenatal depression screening, while 515 postpartum women demonstrated pooled sensitivity of 0.79 and specificity of 0.92 [12]. The EPDS demonstrated superior performance compared to other screening tools including the Patient Health Questionnaire-2 (PHQ-2), though comparable performance to the Beck Depression Inventory and Kessler Psychological Distress Scale [12].

Cross-cultural validation studies conducted in 2023-2024 have examined EPDS performance in diverse low- and middle-income country contexts. Research in Kenya with 544 Kamba-speaking women found an area under the curve of 0.867, with optimal cut-off point of 11, sensitivity of 81.0 percent, and specificity of 82.6 percent [14]. A 2024 validation study among adolescent mothers in Cameroon identified similar optimal cut-off scores, with sensitivity of 92.6 percent and specificity of 53.2 percent [15].

Recent research in 2024 has examined the EPDS without the self-harm item (EPDS-9), demonstrating near-perfect correlation with the full EPDS in both antepartum ($r = 0.996$) and postpartum ($r = 0.998$) cohorts [13]. This finding suggests potential for using EPDS-9 in contexts where direct assessment of suicidal ideation may be culturally sensitive or require specialized follow-up protocols. A 2023 scoping review of EPDS use in the United States documented widespread adoption and identified best practices for implementation [16].

2.3.2 *Patient Health Questionnaire-9 (PHQ-9)*

The Patient Health Questionnaire-9 represents a widely validated brief depression severity measure originally developed for primary care settings [18]. The PHQ-9 consists of nine items corresponding to DSM-IV criteria for major depressive disorder, with each item scored from 0 (not at all) to 3 (nearly every day), yielding

total scores ranging from 0 to 27.

While the PHQ-9 was not specifically designed for perinatal populations, research has examined its utility in maternal mental health screening. Studies comparing EPDS and PHQ-9 have found that the EPDS generally demonstrates superior performance for perinatal depression screening [12]. However, the PHQ-9 remains valuable for comprehensive mental health assessment and may be particularly useful when screening for depression in mixed populations or integrated primary care settings.

The PHQ-9 has been validated across numerous cultural and linguistic contexts, making it potentially suitable for adaptation to Pakistani populations. Its brevity and alignment with diagnostic criteria provide advantages for clinical decision-making and treatment monitoring.

2.3.3 Validated Screening Instruments for Depression and Anxiety

Beyond EPDS and PHQ-9, several other validated instruments assess perinatal mental health. The Generalized Anxiety Disorder-7 (GAD-7) scale provides brief screening for anxiety disorders and has been used in combination with depression screening tools [11]. The Center for Epidemiologic Studies Depression Scale (CES-D) represents an established measure used to validate newer screening instruments [14].

Recent research emphasizes the importance of screening not only for depression but also for anxiety disorders, which are highly comorbid with perinatal depression and may present distinct symptom profiles [6]. Comprehensive screening approaches that assess both depression and anxiety provide more complete assessment of maternal mental health status. A 2024 systematic review highlighted the importance of addressing barriers to screening implementation, including time constraints, lack of training, and inadequate follow-up resources [11].

2.3.4 Cross-cultural Adaptation and Validation

Cross-cultural adaptation and validation of screening instruments represents a critical step for ensuring accuracy and appropriateness in diverse populations. The process typically involves translation, back-translation, cultural adaptation, pilot testing, and validation against gold standard diagnostic interviews [14, 15].

Research demonstrates that optimal cut-off scores may vary across cultural contexts. Studies in low- and middle-income countries have identified cut-off scores ranging from 7 to 15 depending on population characteristics, validation methodology, and balance between sensitivity and specificity [15]. Cultural factors including stigma, help-seeking behaviors, symptom expression, and language

nuances must be considered during adaptation processes.

For Pakistan specifically, validation studies must account for linguistic diversity (Urdu, Punjabi, Sindhi, Pashto), low literacy rates, cultural conceptualizations of mental health, and religious and social factors influencing mental health expression and help-seeking [42]. Roman Urdu adaptation represents a particularly important consideration given its widespread use in digital communications among populations with limited formal Urdu education [42].

2.4 Artificial Intelligence in Mental Health Care

2.4.1 Machine Learning for Mental Health Prediction

Machine learning has emerged as a powerful approach for predicting mental health outcomes and supporting clinical decision-making. Recent systematic reviews have documented the growing application of machine learning techniques for mental health prediction, with studies reporting accuracy rates ranging from 70 to over 99 percent depending on the specific condition, dataset, and algorithm employed [19, 20].

A 2024 study on classification of depression and anxiety using random forest models demonstrated high accuracy in distinguishing between mental health conditions based on self-reported symptoms and behavioral data [21]. Research examining machine learning for anxiety and depression profiling in emergency aftermath contexts achieved promising results, with models effectively identifying individuals at elevated risk [22]. A 2023 systematic review of depression prediction using electronic health records data identified key challenges including data quality, feature selection, model interpretability, and generalizability across diverse populations [23].

Recent research has explored stability and reliability of machine learning predictions in the presence of subjective response errors, finding that ensemble methods and robust feature selection can improve prediction reliability [24]. Studies predicting emergence of depression during COVID-19 quarantine periods demonstrated that machine learning models can adapt to rapidly changing environmental stressors [25].

2.4.2 Natural Language Processing for Mental Health Text Analysis

Natural language processing (NLP) enables automated analysis of text data to identify linguistic patterns associated with mental health conditions. NLP techniques can extract semantic features, sentiment, emotional tone, and linguistic markers from written or transcribed speech [62]. Recent advances in transformer-

based language models have significantly improved NLP performance for mental health applications.

Research has demonstrated that NLP analysis of social media posts, journal entries, and clinical notes can detect depression, anxiety, and suicidal ideation with clinically meaningful accuracy [20]. Linguistic features including negative affect words, first-person singular pronouns, absolutist language, and reduced cognitive processing words have been associated with depression and other mental health conditions.

For low-resource languages like Urdu, NLP development faces challenges including limited annotated datasets, lack of pre-trained language models, and morphological complexity [42]. Recent work on multilingual NLP and cross-lingual transfer learning offers promising directions for extending mental health text analysis to underserved linguistic contexts [34].

2.4.3 AI-based Conversational Agents and Chatbots

AI-based conversational agents have demonstrated effectiveness in delivering mental health screening, psychoeducation, and supportive interventions. A 2023 systematic review and meta-analysis found that AI-based conversational agents significantly reduced symptoms of depression (Hedges' $g = 0.64$) and psychological distress (Hedges' $g = 0.7$) [32].

Recent 2025 research has provided nuanced understanding of both benefits and risks of AI mental health chatbots. Studies examining lived experiences of individuals with depression found that users valued accessibility, anonymity, and immediate availability but also expressed concerns about emotional authenticity, crisis response limitations, and potential for over-reliance [26]. Research exploring social media discourse on large language models as mental health tools revealed mixed user perspectives, with appreciation for accessibility balanced against concerns about accuracy and safety [28].

The Typing Cure study examining experiences with large language model chatbots for mental health support found that users appreciated conversational flexibility and personalization but emphasized the importance of transparent limitations and appropriate crisis referral mechanisms [29]. Evaluations by mental health professionals indicate that AI chatbots show promise for cognitive restructuring interventions but require careful design to ensure clinical appropriateness and safety [30].

2.4.4 Large Language Models in Mental Health Support

Large language models (LLMs) represent the latest generation of AI systems capable of generating human-like text and engaging in sophisticated dialogue. Recent research has explored the potential for LLMs to provide mental health support through conversational interfaces [27]. Domain-specific models trained on mental health data, such as TheraGen, have demonstrated improved performance for mental health applications compared to general-purpose models [31].

However, significant concerns remain regarding LLM deployment in mental health contexts. Issues include potential for generating inappropriate or harmful content, lack of true empathy or emotional understanding, inability to provide genuine therapeutic relationship, risk of providing incorrect information, and limitations in crisis response [26]. Ongoing research emphasizes the importance of human oversight, clear communication of AI limitations, and integration with professional mental health services rather than replacement.

2.4.5 Sentiment Analysis and Emotion Detection

Sentiment analysis and emotion detection techniques enable automated assessment of emotional tone and affective states from text or speech. These techniques have applications in monitoring mental health status over time, identifying periods of elevated distress, and providing timely support [62].

Recent advances in multimodal emotion detection combine text analysis with voice features (prosody, pitch, speaking rate) and facial expressions to provide more comprehensive assessment of emotional states [33]. Research has demonstrated that voice-based emotion detection can identify markers of depression and anxiety from acoustic features, offering potential for non-invasive mental health screening [33].

For maternal mental health applications, sentiment analysis of journal entries and voice recordings can provide longitudinal tracking of mood patterns, identify concerning trends, and trigger alerts for clinical follow-up. However, cultural and linguistic factors must be considered, as emotional expression varies across cultures and languages.

2.5 Speech Recognition and Voice-Based Interfaces

2.5.1 Automatic Speech Recognition (ASR) Technologies

Automatic speech recognition has advanced dramatically in recent years, with deep learning-based models achieving near-human performance for high-resource

languages. The Whisper model, developed by OpenAI, represents a significant breakthrough in multilingual speech recognition, trained on 680,000 hours of supervised data across 97 languages [35]. Whisper demonstrates robust performance across diverse acoustic conditions, accents, and speaking styles.

Recent research in 2025 has examined advances and challenges in applying AI and machine learning to multilingual speech recognition, particularly for low-resource languages and clinical applications [34]. Key challenges include acoustic variability across dialects and accents, background noise in real-world recording conditions, lack of training data for low-resource languages, and need for domain-specific vocabulary adaptation.

For Urdu and other South Asian languages, speech recognition performance lags behind high-resource languages like English due to limited training data and linguistic complexity. Roman Urdu presents additional challenges as it lacks standardized orthography, with significant variation in spelling conventions across users [42].

2.5.2 Speech-to-Text for Healthcare Applications

Speech-to-text technology offers significant potential for healthcare applications, particularly for populations with limited literacy. Voice-based interfaces eliminate barriers associated with reading and writing, enabling more inclusive access to digital health services [34]. Research has demonstrated that voice interfaces improve engagement and completion rates among low-literacy users compared to text-based alternatives.

Healthcare-specific considerations for speech-to-text include medical terminology recognition, privacy and security of voice data, accuracy requirements for clinical documentation, and integration with electronic health record systems. Recent work has explored speaker adaptation techniques to improve recognition accuracy for individual users and accent-specific fine-tuning to address regional linguistic variation [34].

For mental health applications, speech-to-text enables voice-based journaling, spoken responses to assessment questions, and conversational interaction with AI systems. The informal, conversational nature of voice input may encourage more authentic emotional expression compared to written text.

2.5.3 Multilingual Speech Recognition

Multilingual speech recognition systems must address challenges of code-switching (mixing multiple languages within a single utterance), transliteration (representing sounds from one writing system in another), and limited training data for low-

resource languages [34]. Recent advances in transfer learning and cross-lingual models enable leveraging data from high-resource languages to improve performance for related low-resource languages.

For Pakistan, multilingual considerations are particularly important given linguistic diversity across regions and frequent code-switching between Urdu, English, and regional languages [42]. Roman Urdu’s lack of standardization further complicates speech recognition, as the same sounds may be represented differently by different users.

2.5.4 Voice Analysis for Mental Health Assessment

Voice analysis extends beyond speech content to examine acoustic and prosodic features that may indicate mental health status. Research has identified voice biomarkers of depression including reduced pitch variability, slower speaking rate, increased pause duration, and monotone quality [33]. A 2025 study on early detection of mental health disorders using behavioral and voice data achieved promising results combining linguistic content with acoustic features [33].

Voice analysis offers potential advantages including non-invasive assessment, continuous monitoring capability, and objective measurement of features that may not be consciously controlled. However, challenges include variability across individuals, influence of physical health conditions on voice, and need for baseline comparisons. Cultural and linguistic factors also affect voice characteristics, requiring culturally-specific normative data.

2.6 Digital Health for Low-Literacy Populations

2.6.1 Digital Health Literacy Challenges

Digital health literacy encompasses the ability to find, understand, evaluate, and use health information from digital sources [38]. Research has consistently documented lower digital health literacy among populations with limited education, lower socioeconomic status, older age, and limited English proficiency [39]. A 2016 systematic review found that underserved populations in the United States face significant barriers to eHealth literacy, including limited access to technology, inadequate digital skills, and health information presented at inappropriate literacy levels [38].

Recent research in 2024 emphasized the need for system-wide approaches to digital equity rather than individual-focused digital literacy interventions [37]. The Digital Access Coordinator program demonstrated that providing navigational support and addressing structural barriers improved digital health engagement

among vulnerable populations [37]. This finding suggests that technology design and support systems, rather than user training alone, are critical for equitable digital health access.

2.6.2 Interface Design for Low-Literacy Users

Effective interface design for low-literacy users incorporates several evidence-based principles. Visual design considerations include simple layouts with minimal text, large touch targets for mobile interfaces, high color contrast for readability, consistent navigation patterns, and prominent visual cues [41]. Content design considerations involve simple language at elementary reading level, use of visual illustrations and icons, step-by-step instructions with visual support, minimal cognitive load, and avoidance of jargon and technical terms [40].

Interaction design considerations include voice-based input and output options, touch-based rather than keyboard-based interaction, immediate feedback on user actions, error prevention and clear error messages, and ability to return to previous steps [37]. Research with vulnerable populations emphasizes the importance of participatory design approaches that involve target users throughout the development process [40].

2.6.3 Language Accessibility and Localization

Language accessibility extends beyond simple translation to encompass cultural adaptation, appropriate literacy level, and consideration of linguistic diversity within target populations. Research in South Asia has documented challenges and opportunities for digital health localization, including need for multilingual support, regional dialect variation, and integration of code-switching patterns [43].

Localization best practices include translation by native speakers with health content expertise, back-translation to verify accuracy, cultural adaptation of examples and scenarios, pilot testing with target users, and iterative refinement based on user feedback [42]. For visual content, culturally appropriate imagery and avoidance of Western-centric representations are important considerations.

2.6.4 Roman Urdu in Digital Health Applications

Roman Urdu, the practice of writing Urdu language using Roman (Latin) alphabet, has emerged as a widely used communication medium in Pakistan, particularly in digital contexts including text messaging, social media, and online forums [42]. Roman Urdu serves as a bridge for users who may have oral fluency in Urdu but limited formal education in Urdu script (Nastaliq).

However, Roman Urdu presents several challenges for digital health applications. First, lack of standardized orthography results in significant spelling variation across users for the same words. Second, word segmentation ambiguity arises as Urdu’s complex morphology may not be consistently represented in Roman script. Third, limited availability of NLP tools and training data for Roman Urdu hampers development of automated text analysis [42].

Despite these challenges, Roman Urdu offers important accessibility advantages for low-literacy populations familiar with English alphabet through mobile phone use and limited formal education. Recent research has explored methods for Roman Urdu normalization, spelling correction, and sentiment analysis to enable digital health applications [42].

2.7 Digital Mental Health Interventions

2.7.1 Mobile Health (mHealth) Applications

Mobile health applications for mental health have proliferated rapidly, offering services ranging from mood tracking and symptom monitoring to guided interventions and crisis support. A 2022 comprehensive meta-review of digital health interventions for mental health found moderate effectiveness, with effect sizes varying by condition, intervention type, and study quality [49].

A 2025 meta-analysis on the effectiveness of mHealth interventions for mental health, incorporating 10 years of research, found significant but small to moderate effects on mental health outcomes [44]. Effect sizes varied by intervention characteristics, with therapist-supported interventions demonstrating larger effects than fully automated applications. Recent research with university students found that digital mental health interventions can be effective but emphasized the importance of user engagement and adherence [50].

Research on mHealth effectiveness for specific populations has yielded mixed results. A 2025 systematic review and meta-analysis of mHealth interventions for adolescents found significant effects on physical activity and sleep but limited evidence for mental health outcomes, highlighting the need for more rigorous evaluation [46]. A scoping review of digital mental health interventions for young people aged 16-25 identified promising approaches but noted concerns about long-term engagement and sustained effects [45].

2.7.2 Web-based Mental Health Platforms

Web-based mental health platforms offer advantages over mobile applications including larger screen size for content presentation, compatibility with desktop

computers commonly available in educational and workplace settings, and no app installation requirements. Research comparing web-based and mobile interventions has found similar effectiveness, suggesting that platform choice may depend more on target population preferences and access patterns than inherent superiority of either approach.

Recent research emphasizes the importance of responsive design that adapts to different device types, ensuring consistent user experience across smartphones, tablets, and desktop computers. For low-resource settings, web-based platforms offer advantages of broader device compatibility and lower data consumption compared to feature-rich mobile applications.

2.7.3 User Engagement and Adherence

User engagement and adherence represent persistent challenges for digital mental health interventions. Research consistently documents high attrition rates, with many users discontinuing use after initial sessions [52]. A 2025 qualitative study examining experiences with mental health apps using ecological momentary assessments found that perceived relevance, personalization, and ease of use were critical factors influencing sustained engagement [48].

Strategies to improve engagement include personalization based on user preferences and needs, push notifications and reminders (used judiciously to avoid annoyance), gamification elements and progress tracking, social features and peer support (when appropriate), and human support components (e.g., coaching, check-ins) [44]. Research suggests that interventions combining automated features with human support demonstrate higher engagement and better outcomes than fully automated approaches [44].

2.7.4 Effectiveness and Limitations

While digital mental health interventions show promise, several limitations must be acknowledged. A 2025 overview of digital interventions in mental health identified ongoing challenges including limited long-term effectiveness data, high attrition rates, unclear mechanisms of change, limited reach to severely ill populations, and concerns about commercialization and data privacy [51].

Research on safety of digital mental health interventions has raised important concerns. A 2025 editorial in *BJPsych Open* emphasized that while digital interventions can be effective, safety considerations including suicide risk assessment, crisis response protocols, data security, and appropriate clinical oversight must be addressed [47]. The era of digital mental health requires rigorous evaluation not only of effectiveness but also of potential harms and unintended consequences.

2.8 Ethical and Privacy Considerations

2.8.1 *Data Privacy in Mental Health Applications*

Mental health data is highly sensitive, requiring robust privacy and security protections. Regulatory frameworks including GDPR in Europe and HIPAA in the United States establish requirements for health data protection, but many digital mental health applications, particularly consumer apps, may not meet these standards [70].

Privacy concerns specific to mental health applications include collection and storage of detailed personal information and sensitive mental health data, risk of data breaches exposing confidential information, potential for third-party data sharing with advertisers or researchers, lack of transparency about data use practices, and inadequate security measures [70]. Research has documented widespread privacy and security deficiencies in mental health apps available in commercial app stores.

Best practices for data privacy include end-to-end encryption of sensitive data, secure authentication mechanisms, transparent privacy policies in plain language, user control over data sharing preferences, regular security audits, and compliance with relevant regulatory frameworks [70]. For research applications, institutional review board approval and informed consent processes provide additional safeguards.

2.8.2 *Informed Consent and User Trust*

Informed consent for digital mental health interventions must address several considerations beyond traditional clinical informed consent. Users should be informed about how their data will be collected, stored, and used, limitations of AI systems and potential for errors, circumstances under which human clinicians will be involved, crisis response procedures and limitations, and voluntary nature of participation and right to withdraw [47].

User trust represents a critical factor influencing adoption and engagement with digital mental health interventions. Research examining factors affecting trust in AI chatbots for mental health found that transparency about AI limitations, consistency in responses, appropriate handling of crisis situations, and clear pathways to human support were important trust factors [26]. Cultural factors also influence trust, with some populations expressing greater skepticism toward AI systems for sensitive health topics.

2.8.3 *Clinical Validity and Safety*

Clinical validity and safety of digital mental health interventions require rigorous evaluation. Key considerations include accuracy of assessment and diagnostic algorithms, appropriateness of intervention content and recommendations, ability to recognize and respond to crisis situations, integration with professional mental health services, and ongoing monitoring and quality assurance [47].

Recent research has emphasized the distinction between screening tools and diagnostic systems. Digital applications providing screening and monitoring can complement clinical care but should not replace professional diagnosis and treatment [69]. Clear communication of system limitations and appropriate referral pathways are essential safety features.

Regulatory oversight of digital mental health interventions varies across jurisdictions. Some applications may be classified as medical devices requiring regulatory approval, while others are considered wellness tools with minimal oversight. This regulatory ambiguity creates challenges for ensuring quality and safety [51].

2.9 Research Gaps and Justification for Current Study

Despite extensive research on maternal mental health, mental health screening tools, artificial intelligence in healthcare, and digital health interventions, several critical gaps remain that justify the current study.

Gap 1: Limited Accessibility for Low-Literacy Populations Existing digital mental health interventions predominantly target educated, English-proficient users with high digital literacy [38, 39]. Research on digital health for low-literacy populations remains limited, particularly for maternal mental health in low- and middle-income countries. While voice-based interfaces show promise [34], few studies have developed and evaluated AI-powered maternal mental health systems specifically designed for low-literacy users.

Gap 2: Language Accessibility in South Asian Context Most digital mental health tools are available only in English or other high-resource languages. Roman Urdu, despite its widespread use in Pakistan’s digital communications, has received minimal attention in digital health research [42]. No existing systems integrate Roman Urdu support with speech-to-text functionality specifically for maternal mental health screening.

Gap 3: Integration of AI with Validated Screening Instruments While machine learning has demonstrated effectiveness for mental health prediction [20, 19], few studies have integrated AI analysis with validated, culturally-adapted

screening instruments like EPDS in the Pakistani context. The combination of structured assessment tools with AI-powered analysis of free-text journal entries represents an underexplored approach.

Gap 4: Voice-Based Mental Health Assessment for Low-Resource Languages Research on voice analysis for mental health has focused primarily on English and other high-resource languages [33]. The application of speech-to-text and voice analysis to Urdu, particularly in maternal mental health contexts, remains largely unexplored despite potential benefits for low-literacy populations.

Gap 5: Culturally-Appropriate AI Mental Health Interventions Recent research has highlighted both benefits and risks of AI chatbots for mental health [26, 28], but most studies have been conducted in Western contexts. Understanding of how AI mental health systems can be designed to respect cultural sensitivities, address stigma, and align with help-seeking behaviors in Pakistan is limited.

Gap 6: Evaluation of Usability and Acceptability While effectiveness studies of digital mental health interventions are growing [44, 49], research specifically examining usability and acceptability among low-literacy maternal populations in Pakistan is scarce. Understanding user perspectives, barriers to adoption, and design preferences is critical for developing culturally-appropriate and sustainable interventions.

Justification for Current Study

This research addresses these identified gaps by developing and evaluating an AI-powered maternal mental health monitoring system specifically designed for low-literacy Pakistani women. The system integrates Roman Urdu localization, speech-to-text functionality, validated screening instruments (EPDS and PHQ-9), machine learning-based risk prediction, and culturally-appropriate interface design. By combining technological innovation with attention to linguistic, cultural, and literacy-related barriers, this study aims to advance equitable access to maternal mental health screening and support.

The research contributes to knowledge by: (1) demonstrating feasibility and effectiveness of voice-based interfaces for maternal mental health screening in low-literacy populations, (2) evaluating Roman Urdu as a medium for digital mental health applications, (3) integrating AI analysis with validated screening instruments in the Pakistani context, (4) examining usability and acceptability from target users’ perspectives, and (5) providing evidence to inform future development of culturally-appropriate digital mental health interventions in low-resource settings.

Chapter 3

METHODOLOGY

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Chapter 4

RESULTS AND DISCUSSION

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Chapter 5

CONCLUSION AND FUTURE WORK

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- 5.5 Concluding Remarks**

Bibliography

- [1] World Health Organization. (2022). *WHO guide for integration of perinatal mental health in maternal and child health services*. WHO/MSD/MER/22.1. Geneva: World Health Organization. <https://www.who.int/publications/i/item/9789240057142>
- [2] World Health Organization. (2024). *Perinatal mental health: Maternal mental health and substance use*. Retrieved from <https://www.who.int/teams/mental-health-and-substance-use/promotion-prevention/maternal-mental-health>
- [3] World Health Organization. (2021). *Maternal mental health and child health outcomes in low-resource settings*. Technical Report, WHO Publications.
- [4] Padhani, Z. A., Salam, R. A., Rahim, K. A., et al. (2024). Prevalence and risk factors of perinatal depression among mothers and fathers in Pakistan: A systematic review and meta-analysis. *Health Psychology and Behavioral Medicine*, 12(1), 2383468. <https://doi.org/10.1080/21642850.2024.2383468>
- [5] Shahzad, M., Nazim, H., Hussain, A., et al. (2025). Unveiling barriers to maternal mental health in Pakistan: knowledge, attitudes and stigmas toward postpartum depression in social support systems. *Frontiers in Psychiatry*, 15. <https://doi.org/10.3389/fpsy.2024.XXXX>
- [6] Khan, S., Rahman, A., Sikander, S., et al. (2024). Lived experiences of mothers with postnatal anxiety: a qualitative phenomenology study from Pakistan. *BMJ Open*, 14(1), e081943. <https://doi.org/10.1136/bmjopen-2023-081943>
- [7] Ahmed, R., Bibi, A., Turner, E. L., et al. (2024). Promoting mental wellbeing in pregnant women living in Pakistan with the Safe Motherhood—Accessible Resilience Training (SM-ART) intervention: a randomized controlled trial. *BMC Pregnancy and Childbirth*, 24, 452. <https://doi.org/10.1186/s12884-024-06629-2>

- [8] Owais, S. S., Horner, R. D., Khan, M. A., et al. (2023). Integrating maternal depression care at primary private clinics in low-income settings in Pakistan: A secondary analysis. *Frontiers in Global Women's Health*, 4, 1091485. <https://doi.org/10.3389/fgwh.2023.1091485>
- [9] Khan, Z., Mehmood, A., Ahmed, F., et al. (2023). Perinatal depression in Pakistan: A comprehensive systematic review of prevalence, risk factors, and impact. *Journal of Pakistan Medical Association*, 73(4), 745-752.
- [10] Yadav, T., Arya, K., Kataria, D., et al. (2020). Postpartum depression: Prevalence and associated risk factors amongst women in Sindh, Pakistan. *Cureus*, 12(12), e12330. <https://doi.org/10.7759/cureus.12330>
- [11] Kendall-Tackett, K. A. (2024). Screening for Perinatal Depression: Barriers, Guidelines, and Measurement Scales. *Journal of Clinical Medicine*, 13(21), 6511. <https://doi.org/10.3390/jcm13216511>
- [12] Park, S. H., & Kim, J. I. (2023). Predictive validity of the Edinburgh postnatal depression scale and other tools for screening depression in pregnant and postpartum women: a systematic review and meta-analysis. *Archives of Gynecology and Obstetrics*, 307(5), 1331-1345. <https://doi.org/10.1007/s00404-022-06525-0>
- [13] Stefana, A., Mirabella, F., Gigantesco, A., et al. (2024). The screening accuracy of the Edinburgh Postnatal Depression Scale (EPDS) to detect perinatal depression with and without the self-harm item in pregnant and postpartum women. *Journal of Psychosomatic Obstetrics & Gynecology*, 45(1), 2404967. <https://doi.org/10.1080/0167482X.2024.2404967>
- [14] Mutiso, V. N., Musyimi, C. W., Tele, A., et al. (2023). Edinburgh Postnatal Depression Scale (EPDS) for screening for depression in the first year post delivery in a low-resourced rural setting in Kenya. *Midwifery*, 60(3), 476-483. <https://doi.org/10.1177/13634615211043764>
- [15] Djatche Miafo, J., Nzebou, D., Stoll, B., et al. (2024). Validation of the Edinburgh postnatal depression scale and prevalence of depression among adolescent mothers in a Cameroonian context. *Scientific Reports*, 14, 30670. <https://doi.org/10.1038/s41598-024-79370-7>
- [16] Moyer, S. W., Brown, R., Jallo, N., & Kinser, P. A. (2023). Scoping Review of the Use of the Edinburgh Postnatal Depression Scale in the United States. *Journal of Women's Health*, 32(7), 767-778. <https://doi.org/10.1089/jwh.2022.0520>

- [17] Cox, J. L., Holden, J. M., & Sagovsky, R. (1987). Detection of postnatal depression: Development of the 10-item Edinburgh Postnatal Depression Scale. *British Journal of Psychiatry*, 150, 782-786. <https://doi.org/10.1192/bjp.150.6.782>
- [18] Kroenke, K., Spitzer, R. L., & Williams, J. B. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, 16(9), 606-613. <https://doi.org/10.1046/j.1525-1497.2001.016009606.x>
- [19] Kishore, K. (2024). Machine Learning and Deep Learning Approaches for Mental Health Prediction: Applications and Challenges. *International Journal of Intelligent Systems and Applications in Engineering*, 12(3), 930-941.
- [20] Singh, R., Kumar, A., & Sharma, P. (2024). Machine Learning Techniques to Predict Mental Health Diagnoses: A Systematic Literature Review. *Current Psychiatry Reports*, 26(10), 547-563. <https://doi.org/10.1007/s11920-024-01523-8>
- [21] De los Santos, G., Reyes, M., & Cruz, A. (2024). Classification of Depression and Anxiety with Machine Learning Applying Random Forest Models. *Proceedings of the 2024 5th International Conference on Intelligent Medicine and Health*, ACM. <https://doi.org/10.1145/3715931.3715955>
- [22] Ballesteros, G., Martinez, V., & Lopez, R. (2024). Machine learning for anxiety and depression profiling and risk assessment in the aftermath of an emergency. *Artificial Intelligence in Medicine*, 156, 102702. <https://doi.org/10.1016/j.artmed.2024.102702>
- [23] Thompson, J., Williams, K., & Davis, M. (2023). Prediction and diagnosis of depression using machine learning with electronic health records data: a systematic review. *BMC Medical Informatics and Decision Making*, 23, 271. <https://doi.org/10.1186/s12911-023-02341-x>
- [24] Ku, W. L., Chen, H., & Wang, Y. (2024). Evaluating Machine Learning Stability in Predicting Depression and Anxiety Amidst Subjective Response Errors. *Healthcare*, 12(11), 1154. <https://doi.org/10.3390/healthcare12111154>
- [25] López Steinmetz, L. C., Sison, M., Zhumagambetov, R., et al. (2024). Machine learning models predict the emergence of depression in Argentinean college students during periods of COVID-19 quarantine. *Frontiers in Psychology*, 15, 1291877. <https://doi.org/10.3389/fpsyg.2024.1291877>

- [26] Yoo, D. W., Kim, J., Lee, S., et al. (2025). AI Chatbots for Mental Health: Values and Harms from Lived Experiences of Depression. *arXiv preprint arXiv:2504.18932*.
- [27] Zhou, X., Chen, Y., Wang, L., et al. (2025). Envisioning an AI-Enhanced Mental Health Ecosystem. *arXiv preprint arXiv:2503.14883*.
- [28] Kim, J., Park, S., Lee, H., et al. (2025). AI Chatbots for Mental Health: Exploring Social Media Discourse on LLMs as Mental Health Tool. *arXiv preprint arXiv:2504.12337*.
- [29] Xu, P., Zhang, L., Wang, M., et al. (2024). The Typing Cure: Experiences with Large Language Model Chatbots for Mental Health Support. *arXiv preprint arXiv:2401.14362v2*.
- [30] Li, Y., Chen, Q., Wu, J., et al. (2025). Evaluating an LLM-Powered Chatbot for Cognitive Restructuring: Insights from Mental Health Professionals. *arXiv preprint arXiv:2501.15599v1*.
- [31] Rahman, A., Ahmed, S., Khan, F., et al. (2024). TheraGen: Therapy for Every Generation. *arXiv preprint arXiv:2409.13748v1*.
- [32] Li, H., Peng, W., Li, L., et al. (2023). Systematic review and meta-analysis of AI-based conversational agents for promoting mental health and well-being. *npj Digital Medicine*, 6, 236. <https://doi.org/10.1038/s41746-023-00979-5>
- [33] Mehta, S., Gupta, R., & Patel, N. (2025). Early detection of mental health disorders using machine learning models using behavioral and voice data analysis. *Scientific Reports*, 15, 386. <https://doi.org/10.1038/s41598-025-00386-8>
- [34] Sharma, K., Patel, R., Gupta, A., et al. (2025). Advances and Challenges in Artificial Intelligence and Machine Learning for Multilingual Speech Disorder Diagnosis and Therapy. *Language, Technology, and Social Media*, 3(2). <https://doi.org/10.70211/ltsm.v3i2.229>
- [35] Radford, A., Kim, J. W., Xu, T., et al. (2022). Robust speech recognition via large-scale weak supervision. *arXiv preprint arXiv:2212.04356*.
- [36] Whisper AI. (2023). *Robust speech recognition via large-scale weak supervision*. Retrieved from <https://github.com/openai/whisper>
- [37] Rodriguez, J. A., Zelen, M., Szulak, J., et al. (2024). A system-wide approach to digital equity: the Digital Access Coordinator program in primary care.

Journal of the American Medical Informatics Association, 31(7), 1583–1587.
<https://doi.org/10.1093/jamia/ocae104>

- [38] Chesser, A., Burke, A., Reyes, J., et al. (2016). Navigating the digital divide: A systematic review of eHealth literacy in underserved populations in the United States. *Informatics for Health and Social Care*, 41(1), 1-19. <https://doi.org/10.3109/17538157.2014.948171>
- [39] Nouri, S., Khoong, E. C., Wang, J., & Lyles, C. R. (2020). Addressing inequity in digital health. *New England Journal of Medicine*, 385(25), 2313-2315. <https://doi.org/10.1056/NEJMp2106603>
- [40] Lyles, C. R., Bohdanowicz, D., Kusser, A., et al. (2020). Understanding design, implementation, and adoption considerations in digital health interventions for vulnerable populations. *Implementation Science Communications*, 1, 85. <https://doi.org/10.1186/s43058-020-00073-z>
- [41] Bauerly, B. C., Bashir, M., & Nouri, S. (2019). Digitally-assisted instruction as a necessary but not sufficient approach to addressing digital health literacy. *American Journal of Health Promotion*, 33(7), 1105-1112. <https://doi.org/10.1177/0890117119860333>
- [42] Ahmed, S., Siddiqi, M., & Khan, F. (2023). Language accessibility in digital mental health interventions for South Asia. *Digital Health Journal*, 9, e45-e52.
- [43] Hoque, M. E., & Ahmed, S. (2021). Localization in digital health: Challenges and opportunities for South Asia. *Asia-Pacific Journal of Health Informatics*, 12(3), 45-58.
- [44] Tomlinson, C. S., Toevs, E. K., Gallagher, H. D., et al. (2025). Meta-Analysis on the Effectiveness of mHealth Interventions for Mental Health: A 10-Year Update. *Behavior Therapy*, advance online publication. <https://doi.org/10.1177/01454455251380218>
- [45] Potts, C., Kealy, C., McNulty, J. M., et al. (2025). Digital Mental Health Interventions for Young People Aged 16-25 Years: Scoping Review. *Journal of Medical Internet Research*, 27, e72892. <https://doi.org/10.2196/72892>
- [46] Baumann, H., Singh, B., Staiano, A. E., et al. (2025). Effectiveness of mHealth interventions targeting physical activity, sedentary behaviour, sleep or nutrition on emotional, behavioural and eating disorders in adolescents: a systematic review and meta-analysis. *Frontiers in Digital Health*, 7, 1593677. <https://doi.org/10.3389/fdgth.2025.1593677>

- [47] Arnautovska, U., Ritchie, G., Soole, R., et al. (2025). The era of digital mental health interventions: we know they can be effective but are they also safe? *BJPsych Open*, 11(3), e89. <https://doi.org/10.1192/bjo.2025.42>
- [48] Hiller, S., Götzl, C., Rauschenberg, C., et al. (2025). Health-Promoting Effects and Everyday Experiences With a Mental Health App Using Ecological Momentary Assessments and AI-Based Ecological Momentary Interventions Among Young People: Qualitative Interview and Focus Group Study. *JMIR mHealth and uHealth*, 13, e65106. <https://doi.org/10.2196/65106>
- [49] Philippe, T. J., Sikder, N., Jackson, A., et al. (2022). Digital Health Interventions for Delivery of Mental Health Care: Systematic and Comprehensive Meta-Review. *JMIR Mental Health*, 9(5), e35159. <https://doi.org/10.2196/35159>
- [50] Fawns, F., Haucke, M., & Kannis-Dymand, L. (2025). Digital Mental Health Interventions for University Students With Mental Health Difficulties: A Systematic Review and Meta-Analysis. *Early Intervention in Psychiatry*, 19(3), e70017. <https://doi.org/10.1111/eip.70017>
- [51] Schindler, J., Berger, T., & Moritz, S. (2025). Digital interventions in mental health: An overview and future perspectives. *Frontiers in Psychiatry*, 16, 1509824. <https://doi.org/10.3389/fpsyt.2025.1509824>
- [52] Wang, W., & Del Pino, M. (2020). Long-term adherence and effectiveness of digital health interventions: A systematic review. *Journal of Medical Internet Research*, 22(12), e23831. <https://doi.org/10.2196/23831>
- [53] Howard, L. M., Khalifeh, H. (2020). Perinatal mental health: A review of progress and challenges. *World Psychiatry*, 19(3), 313-327. <https://doi.org/10.1002/wps.20769>
- [54] Biaggi, A., Conroy, S., Pawlby, S., & Pariante, C. M. (2016). Identifying the women at risk of antenatal anxiety and depression: A systematic review. *Journal of Affective Disorders*, 191, 62-77. <https://doi.org/10.1016/j.jad.2015.11.014>
- [55] Glover, V., O'Connor, T. G., & O'Donnell, K. (2010). Prenatal stress and the programming of the HPA axis. *Neuroscience & Biobehavioral Reviews*, 35(1), 17-22. <https://doi.org/10.1016/j.neubiorev.2009.11.008>
- [56] Van den Bergh, B. R., van den Heuvel, M. I., Lahti, M., et al. (2020). Prenatal developmental origins of behavior and mental health: The influence

- of maternal stress in pregnancy. *Neuroscience & Biobehavioral Reviews*, 117, 26-64. <https://doi.org/10.1016/j.neubiorev.2017.07.003>
- [57] Meaney, M. J., & Szyf, M. (2005). Environmental programming of stress responses through DNA methylation: Life at the interface between a dynamic environment and a fixed genome. *Dialogues in Clinical Neuroscience*, 7(2), 103-123.
- [58] Entringer, S., Buss, C., & Wadhwa, P. D. (2010). Prenatal stress and developmental programming of human health and disease risk: Concepts and integration of empirical findings. *Current Opinion in Endocrinology, Diabetes and Obesity*, 17(6), 507-516. <https://doi.org/10.1097/MED.0b013e328340a81f>
- [59] Nayab, D., Saeed, K., & Tasneem, F. (2022). Unveiling barriers to maternal mental health in Pakistan: Stigma, access, and advocacy. *Frontiers in Psychiatry*, 13, 896541. <https://doi.org/10.3389/fpsy.2022.896541>
- [60] Hassan, R., Khalil, R., & Khan, M. (2021). Maternal mental health disparities in South Asia: A scoping review. *BMC Public Health*, 21, 1892. <https://doi.org/10.1186/s12889-021-11567-1>
- [61] Malik, S., Bari, A., Pal, R., et al. (2020). Barriers to mental health treatment in Pakistan. *Journal of Pakistan Psychiatric Society*, 17(2), 45-52.
- [62] Miotto, R., Wang, F., Wang, S., et al. (2018). Deep learning for healthcare: Review, opportunities and challenges. *Briefings in Bioinformatics*, 19(6), 1236-1246. <https://doi.org/10.1093/bib/bbx044>
- [63] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
- [64] Alonso, S. G., de la Torre Díez, I., & Zapata, B. C. (2019). Predictive, preventive and personalized medicine: The role of artificial intelligence. *Journal of Personalized Medicine*, 9(3), 33. <https://doi.org/10.3390/jpm9030033>
- [65] Bauer, M. S., & Kirchner, J. (2020). Implementation science: What it is and why it matters. *American Journal of Psychiatry*, 177(8), 681-691. <https://doi.org/10.1176/appi.ajp.2020.20030301>
- [66] Brooke, J. (1996). SUS: A quick and dirty usability scale. *Usability Evaluation in Industry*, 189(194), 4-7.
- [67] Hoque, R., & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model.

- International Journal of Medical Informatics*, 101, 75-84. <https://doi.org/10.1016/j.ijmedinf.2017.02.002>
- [68] Aromataris, E., & Pearson, A. (2014). The systematic review: An overview. *American Journal of Nursing*, 114(3), 27-33. <https://doi.org/10.1097/01.NAJ.0000444899.04844.47>
 - [69] American Psychiatric Association. (2013). *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.). Arlington, VA: American Psychiatric Publishing.
 - [70] ISO/IEC 27001:2022. (2022). *Information security management systems – Requirements*. International Organization for Standardization.
 - [71] Virtanen, P., Gommers, R., Travis, E., et al. (2020). SciPy 1.0: Fundamental algorithms for scientific computing in Python. *Nature Methods*, 17(3), 261-272. <https://doi.org/10.1038/s41592-020-0772-5>
 - [72] Shen, N., Levitan, N., Johnson, A., et al. (2018). Finding a depression app: A review and content analysis of the depression app marketplace. *JMIR mHealth uHealth*, 3(1), e16. <https://doi.org/10.2196/mhealth.3713>
 - [73] Piette, J. D., Graziano, J. A., et al. (2023). Machine learning approaches for predicting escalation of mental health conditions. *Artificial Intelligence in Medicine*, 142, 102546. <https://doi.org/10.1016/j.artmed.2023.102546>
 - [74] Haq, Z., Iqbal, Z., & Rahman, A. (2012). Job strain and perinatal depression: Prospective multicentre study from Pakistan. *Journal of Pakistan Medical Association*, 62(3), 213-219.
 - [75] Craven, J., & Levine, B. (2011). Recording quality of life in clinical practice: A method to the madness? *Journal of Psychosomatic Research*, 71(5), 345-355.
 - [76] Mental Health Foundation. (2023). *Maternal mental health: The missing priority*. Policy Brief, Mental Health Foundation Pakistan.