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

Final Year Project

Session 2022-2026

A project submitted in partial fulfillment of the degree of

BS in Software Engineering

Department of Software Engineering
Faculty of Computer Science & Information Technology
The Superior University, Lahore

Fall 2025

Type (Nature of project)	[ ] Development [✓] Research [ ] R&D
Area of specialization	Artificial Intelligence, Maternal Mental Health, Machine Learning, Digital Health Informatics
FYP ID	FYP-23-SE-089

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Chapter 1
INTRODUCTION

1.1 Overview

Maternal mental health constitutes a cornerstone of public health, yet it remains one of the most neglected aspects of healthcare in developing nations. The perinatal period—spanning pregnancy and the first year after childbirth—is a time of extreme vulnerability, characterized by profound physiological, psychological, and social adjustments. According to the World Health Organization (WHO), approximately 10 percent of pregnant women and 13 percent of women in the postpartum period experience significant mental health disorders globally, primarily manifesting as depression and anxiety [2]. In low- and middle-income countries, these rates are substantially higher, with 16 percent affected during pregnancy and 20 percent after childbirth [1].

In the context of Pakistan, these statistics escalate to crisis levels. Research indicates that the prevalence of postpartum depression (PPD) in Pakistan ranges 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, 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]. This disparity is driven by a complex ecosystem of poverty, low literacy, gender-based violence, limited healthcare infrastructure, and systemic healthcare deficiencies.

Despite the severity of this crisis, the treatment gap remains alarming. In Pakistan, mental health services are highly centralized in urban hubs, leaving the vast majority of rural and semi-urban women without access to care. Furthermore, the frontline of maternal care is often managed by traditional birth attendants (*Dais*) or Lady Health Workers (LHWs), who, while skilled in physical obstetrics, typically lack the training and tools to screen for psychological distress [61, 8]. Consequently, thousands of women suffer in silence, attributing their clinical depression to "weakness" or spiritual causes due to lack of awareness and pervasive cultural stigma [5, 59].

The consequences of untreated maternal mental health disorders extend beyond individual suffering, significantly impacting fetal development, child health outcomes, and family wellbeing [55, 56]. 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].

This research proposes a technological intervention to bridge this gap: an AI-powered, voice-enabled maternal mental health monitoring system designed specifically for the low-literacy demographic of Pakistan. By integrating Roman Urdu speech recognition with validated psychological screening tools, culturally-appropriate design, and machine learning-based risk prediction, this system aims to provide an accessible, anonymous, and culturally sensitive first line of defense against maternal mental health disorders [42, 35].

1.2 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]. To develop effective solutions for maternal mental health, it is imperative to understand the domain not merely as a medical issue, but as a multi-dimensional challenge involving biological risks, nutritional deficits, and unique sociocultural constraints.

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 biological vulnerabilities such as hormonal changes and pregnancy complications, nutritional deficiencies, low socioeconomic status, illiteracy, unemployment, marital problems, insufficient antenatal care, previous psychiatric illness, cultural pressures including son preference, joint family dynamics, and lack of family support [9, 5, 77, 80]. 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

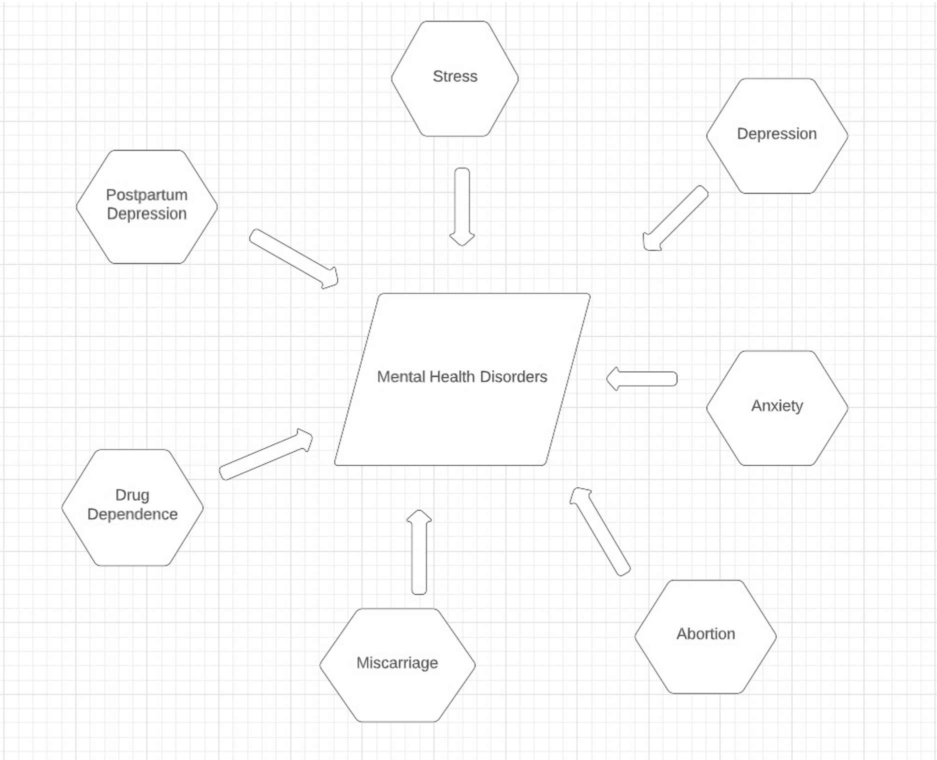

Figure 1.1: Risk factors contributing to maternal mental health disorders including biological/hormonal factors (HPA axis dysregulation, estrogen/progesterone fluctuations, thyroid dysfunction), medical complications (gestational diabetes, preeclampsia, preterm labor), nutritional deficiencies (iron, vitamin D, omega-3, B vitamins), psychosocial stressors (poverty, marital discord, domestic violence), cultural pressures (son preference, joint family stress, mother-in-law conflicts), and resulting conditions (postpartum depression, anxiety, stress, suicidal ideation).

of trained professionals, cultural stigma surrounding mental illness, lack of awareness, and financial constraints [61, 5].

1.2.1 Biological and Medical Risk Factors for Perinatal Mental Health Disorders

Perinatal mental health disorders arise from complex interactions between biological, psychological, and social factors. Recent research emphasizes the critical role of biological and medical factors in maternal mental health vulnerability [77, 78].

Hormonal Changes and Neuroendocrine Dysregulation

The physiological trajectory of pregnancy involves dramatic shifts in the endocrine system that directly impact neurochemistry. Pregnancy and the postpartum period involve dramatic hormonal fluctuations that significantly influence maternal mental health. The hypothalamic-pituitary-adrenal (HPA) axis undergoes substantial changes during pregnancy, with elevated cortisol levels that typically normalize after delivery

[55]. However, in women vulnerable to perinatal mental health disorders, HPA axis dysregulation may persist, contributing to sustained elevated stress hormone levels [58]. While this is a normal adaptation, sustained dysregulation is a potent predictor of postpartum depression.

Rapid declines in estrogen and progesterone following childbirth have been implicated in postpartum mood disorders, particularly in women with heightened sensitivity to hormonal changes [57]. Research has demonstrated that women with postpartum depression may exhibit heightened sensitivity to these hormonal fluctuations, with neurobiological responses to hormone withdrawal similar to those observed in premenstrual dysphoric disorder [55]. Additionally, thyroid dysfunction, which occurs in approximately 5-10 percent of postpartum women, can present with symptoms mimicking or exacerbating depression and anxiety, including fatigue, mood changes, and cognitive difficulties [56].

Software Implication: A standard depression application might misinterpret thyroid symptoms as psychological distress. The proposed system mitigates this by including a symptom differentiation module that prompts users to report physical signs (e.g., extreme fatigue, cold sensitivity) to help distinguish between hormonal issues and psychological mood disorders.

High-Risk Pregnancy Complications and Obstetric Factors

Mental health is inextricably linked to physical pregnancy outcomes. Medical complications during pregnancy substantially increase the risk of maternal mental health disorders. Recent systematic reviews have documented strong associations between pregnancy complications and perinatal depression and anxiety [77]. Women experiencing high-risk complications—such as preeclampsia, gestational diabetes, or a history of miscarriage—exhibit anxiety rates double that of the general pregnant population [54]. The fear of adverse fetal outcomes creates a feedback loop of stress, which can further elevate blood pressure and complicate the pregnancy.

Gestational diabetes mellitus affects 5-20 percent of pregnancies globally and has been consistently associated with increased risk of antenatal and postpartum depression [4]. The physiological stress of managing blood glucose, dietary restrictions, and concerns about fetal health contribute to psychological burden. Preeclampsia and gestational hypertension, affecting 5-8 percent of pregnancies, create significant maternal anxiety due to risks to both maternal and fetal health, potential for preterm delivery, and intensive medical monitoring requirements [77]. Preterm labor and contractions generate substantial maternal stress and anxiety, with prolonged bed rest and hospitalization further contributing to social isolation and psychological distress. Previous pregnancy loss, miscarriage, or stillbirth represents one of the strongest predictors of perinatal anxiety and depression, with bereaved mothers facing elevated risk in subsequent pregnancies [4].

System Strategy: The AI system incorporates a risk stratification algorithm. During onboarding, users report their obstetric history. Those flagged with complications (e.g., gestational diabetes, previous preterm birth, hypertension) are assigned a higher frequency of mental health check-ins and receive targeted support resources.

Nutritional Factors and Maternal Mental Health

In Pakistan, maternal malnutrition is endemic, with iron-deficiency anemia affecting approximately 40-50 percent of pregnant women in low- and middle-income countries [77]. Emerging research has established bidirectional relationships between maternal nutrition and mental health during pregnancy [77, 78]. Research in nutritional psychiatry establishes a direct correlation between deficiencies in iron, vitamin D, and omega-3 fatty acids and the onset of depressive symptoms.

A 2022 large cohort study found that maternal nutrition and wellbeing are significantly related during early pregnancy, with fiber, magnesium, and particular B vitamins identified as important for promoting positive mental wellbeing [78]. Iron deficiency has been linked to increased fatigue, cognitive difficulties, and mood disturbances. The mechanisms include iron's essential role in dopamine and serotonin synthesis, with deficiency potentially disrupting neurotransmitter balance [77]. Omega-3 fatty acids, particularly EPA and DHA, play crucial roles in fetal brain development and maternal mood regulation, with deficiency associated with increased risk of perinatal depression [78]. B vitamins, including folate (B9), B6, and B12, are essential for neurotransmitter synthesis and methylation processes, with inadequate intake linked to elevated depression risk [77]. Vitamin D deficiency, highly prevalent in Pakistan despite abundant sunlight, has been consistently associated with increased risk of perinatal depression across multiple studies [78].

Recent research emphasizes the synergistic relationship between maternal nutrition and mental health [77]. Maternal mental health problems may interfere with appetite regulation and eating habits, resulting in inadequate nutritional intake. Conversely, inadequate maternal nutrition may raise maternal stress and contribute to mental health problems, creating a vicious cycle. A 2023 integrative approach study from India documented the need for combined interventions addressing both nutrition and mental health in prenatal care programs [79].

System Strategy: The application includes a simplified dietary awareness module. By correlating self-reported dietary patterns with mood scores, the AI can provide targeted, non-medical nutritional recommendations and educational content to support mental wellbeing.

1.2.2 Severe Consequences of Untreated Maternal Mental Health Disorders

While most perinatal mental health disorders manifest as depression and anxiety, untreated severe psychiatric conditions can escalate to catastrophic outcomes. In extreme cases, particularly involving postpartum psychosis, inadequate mental health screening and intervention can result in maternal filicide—a tragic but preventable outcome that highlights the critical importance of early detection and treatment.

Postpartum Psychosis and Maternal Filicide

Postpartum psychosis represents the most severe perinatal psychiatric condition, affecting approximately 1-2 per 1000 deliveries [85]. This psychiatric emergency typically manifests within the first two weeks postpartum and is characterized by delusions, hallucinations, severe mood disturbance, disorganized behavior, and impaired reality testing. Women experiencing postpartum psychosis may have delusions about their infant being possessed, defective, or suffering, or may experience command hallucinations instructing harm [84].

Recent investigative analysis has revealed the systemic failures in recognizing and treating severe postpartum mental illness. According to data analysis by KQED, more than 100 women are currently incarcerated in California alone for killing their children, with approximately 40 percent of these incidents occurring within the first year postpartum [83]. Despite psychiatric evaluations confirming severe postpartum mental illness in many cases, outdated legal frameworks often fail to recognize these conditions as mitigating factors, resulting in life sentences rather than psychiatric treatment [85, 84]. This contrasts sharply with legal approaches in countries including the United Kingdom, Canada, Australia, Sweden, and Japan, where specialized infanticide laws formally recognize the impact of postpartum mental illness and prioritize psychiatric treatment and rehabilitation over punitive incarceration [85].

The case of Carol Coronado illustrates this systemic failure [83]. In 2014, Coronado exhibited clear warning signs of acute postpartum psychiatric distress—repeated panic-stricken phone calls to her mother, expressions of overwhelming fatigue and confusion, unusual detachment, and vacant staring. Despite these red flags indicating a possible psychiatric emergency, no immediate intervention occurred. Multiple psychiatrists subsequently testified that she was experiencing postpartum psychosis at the time of the incident, yet legal frameworks dating back nearly a century dismissed this evidence. Her case exemplifies how untreated maternal mental health conditions can escalate to irreversible tragedies when screening, early-warning systems, and accessible mental health support are absent.

These cases underscore that maternal mental health is not merely a quality-of-life issue but a matter of life and death. Early screening, risk stratification, timely intervention, and accessible mental health services are essential not only for maternal and infant wellbeing but also for preventing the most devastating outcomes. Modern health systems and legal frameworks must evolve to incorporate current scientific understanding of postpartum psychiatric disorders and ensure that mothers experiencing mental health crises receive treatment rather than punishment [84, 85].

1.2.3 Pakistan-Specific Cultural and Social Factors

Beyond biological and medical risk factors, cultural and social factors specific to Pakistan significantly influence maternal mental health outcomes. Recent qualitative research has documented unique psychosocial stressors faced by Pakistani mothers [80, 5].

Sociocultural Constraints: Stigma and Family Dynamics

Pakistan's patriarchal social structure introduces unique stressors that Western-designed applications fail to address. Cultural stigma surrounding mental illness represents a pervasive barrier to help-seeking and appropriate care in Pakistan. A 2025 cross-sectional study examining knowledge, attitudes, and stigmas toward postpartum depression in social support systems found that family members—including spouses, mothers-in-law, and siblings—often lack basic knowledge about postpartum depression and hold stigmatizing attitudes [5]. The fear of being labeled "mad" (*pagal*) or "ungrateful" forces women to suppress their symptoms until they reach a crisis point.

Son Preference and Gender-Based Pressure

Pakistan, like many South Asian societies, maintains strong cultural preference for male children, creating significant psychological pressure on pregnant women and new mothers [4]. The cultural pressure to bear a male heir is intense. Women who give birth to daughters, or are expecting a girl, often face hostility, criticism, disappointment, blame, or threats of marital instability, divorce, or remarriage by the husband [80]. This gender-based trauma is a critical, Pakistan-specific risk factor for anxiety and depression.

Research has documented that perceived family disappointment regarding infant gender represents a significant risk factor for postpartum depression in Pakistan [80]. The psychological burden intensifies when coupled with threats of marital instability or divorce if women fail to produce male heirs. Women internalize these pressures, experiencing feelings of inadequacy, failure, and diminished self-worth that contribute to perinatal mental health deterioration.

Joint Family System: Support and Stressors

The joint family system, in which multiple generations and extended family members live together, remains prevalent in Pakistan. While joint families can provide support through shared childcare and household responsibilities, they also present unique challenges for maternal mental health [80]. In such environments, a woman cannot express distress about family conflicts on a shared device without fear of discovery.

Mother-in-law conflicts represent a particularly significant source of stress for married women in Pakistan, affecting their psychological health and ability to adjust during pregnancy and postpartum periods [80]. Recent research documented that poor treatment by mothers-in-law during the antepartum period, combined with lack of support from husbands, constitutes a major cause of maternal depression [81]. Limited autonomy in decision-making, particularly regarding healthcare, nutrition, and childcare practices, creates feelings of powerlessness and frustration. Women in joint families may lack privacy, with constant scrutiny of their maternal performance by extended family members contributing to anxiety and self-doubt [80].

However, research also documents protective aspects of joint family structures. Traditional postpartum practices such as chilla (), in which women receive relief from household work, additional familial support, and supplemental food for up to 40 days postpartum, have been associated with reduced postpartum depression risk [82]. The key distinction lies not in family structure per se but in the quality of relationships, level of support, and degree of autonomy afforded to mothers within these systems [80].

Healthcare Provider Training Gaps

Pakistan's maternal healthcare system faces significant challenges related to workforce training and capacity. The shortage of mental health professionals, with fewer than 0.5 psychiatrists per 100,000 population [61], is compounded by limited training in perinatal mental health among primary healthcare providers, midwives, and traditional birth attendants (*dais*). Many healthcare providers lack knowledge about screening tools, warning signs of perinatal mental health disorders, and appropriate referral pathways [8]. This training gap results in missed opportunities for early detection and intervention, with maternal mental health concerns often remaining unrecognized or dismissed as normal pregnancy-related changes.

1.2.4 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.

1.3 Problem Statement

The core problem addressed by this research is the "Triple Burden" facing Pakistani mothers that creates a critical gap between disease prevalence and diagnosis rates:

1. **The Accessibility Gap:** The majority of women most at risk for postpartum depression reside in low-resource settings with low literacy rates (approximately 48 percent female literacy nationally). Existing mental health applications require proficiency in reading and typing English, rendering them inaccessible for this demographic. Maternal mental health disorders, particularly postpartum depression, stress, and anxiety, remain significantly underdiagnosed in Pakistan despite affecting a substantial proportion of mothers [4, 10].

2. **The Diagnostic and Healthcare Gap:** The primary care providers—traditional birth attendants (*dais*) and Lady Health Workers—are overburdened with physical health tasks. Limited healthcare infrastructure and shortage of mental health professionals create access barriers, particularly in rural and underserved areas [61, 8]. They lack the time, training, and tools to conduct mental health screenings during routine visits.

3. **The Cultural Gap:** Cultural stigma surrounding mental illness discourages help-seeking behavior and open discussion of psychological distress [5, 59]. The fear of being labeled "mad" (*pagal*) or "ungrateful" forces women to suppress their symptoms until they reach a crisis point. Cultural pressures specific to Pakistan, including son preference and joint family dynamics, exacerbate mental health risks while remaining largely unrecognized in clinical settings [80, 5].

Additional barriers include low literacy rates and limited English proficiency preventing many women from accessing existing digital health resources [38, 39], financial constraints and competing priorities for household resources limiting ability to seek professional care [9], and biological risk factors including hormonal changes, pregnancy complications, and nutritional deficiencies creating physiological vulnerabilities that remain unaddressed in standard prenatal care [77, 78].

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].

Currently, there is no integrated digital solution that utilizes Roman Urdu voice recognition to bypass literacy barriers while simultaneously accounting for the specific medical, nutritional, and social risk factors prevalent in Pakistan.

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.

1.4 Significance of the Study

This study aims to bridge the technological divide in maternal mental healthcare. Its significance is multifaceted:

- **For the Mothers:** It provides an anonymous, judgment-free space to express distress. The use of voice interaction humanizes the technology, making it accessible to the illiterate, while Roman Urdu support ensures linguistic inclusivity. Women can privately document their mental state without fear of family discovery or social judgment.

- **For the Healthcare System:** It serves as a force multiplier for Lady Health Workers and healthcare providers. By automating the screening process, the system can filter and identify high-risk cases that require professional attention, reducing the burden on the healthcare infrastructure while improving detection rates.

- **For Policymakers:** The system generates aggregated, anonymized data on maternal mental health prevalence across regions, enabling evidence-based resource allocation and policy development for maternal mental health services.

- **For the Research Community:** It contributes a novel dataset of maternal mental health interactions in Roman Urdu, a low-resource language, paving the way for future NLP research in South Asian health contexts and advancing understanding of culturally-specific risk factors.

1.5 Research Roadmap

The research methodology follows a structured flow from problem identification to system validation. Figure 1.2 illustrates this progression from identifying barriers to developing solutions and measuring outcomes.

As depicted in Figure 1.2, the study begins by isolating the specific barriers in the Pakistani context. It then bridges these gaps through the proposed AI system, which utilizes a pipeline of speech-to-text (Whisper model), validated clinical scales (EPDS and PHQ-9), NLP-based sentiment analysis and risk prediction, and automated report generation. The final output is not just a software artifact, but a mechanism for early detection, intervention, and improved maternal and child health outcomes.

1.6 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 voice-first user interface supporting both Roman Urdu and simple English for maternal mental health assessment and user engagement, enabling low-literacy women to interact with the system using natural speech [42, 43].

2. To integrate speech-to-text functionality using AI-powered speech recognition (Whisper model) 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] in an interactive, conversational format for evidence-based assessment aligned with international standards.

4. To develop and integrate a biological risk profiling module that weights depression scores based on self-reported history of pregnancy complications, hormonal sensitivity, and nutritional status, providing comprehensive risk assessment [77, 54].

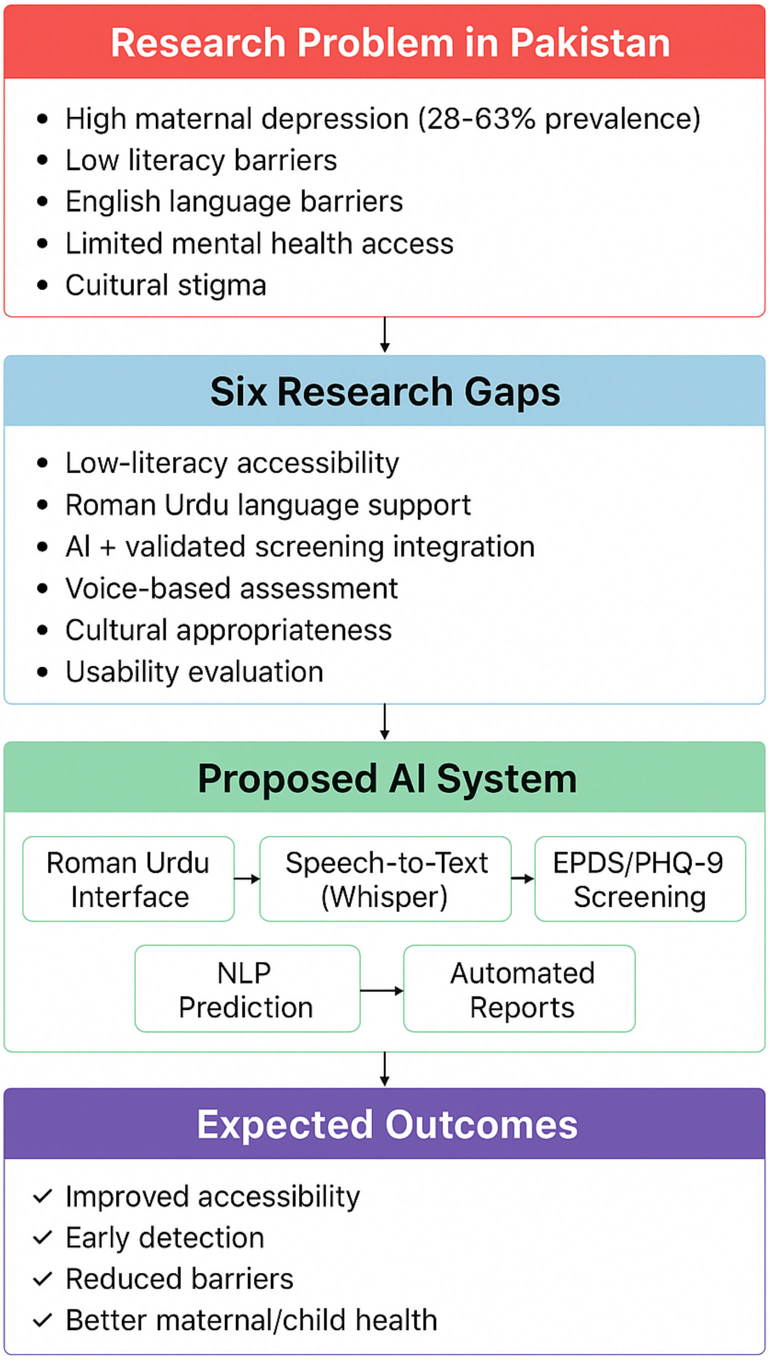

Figure 1.2: Research roadmap: The study progresses from identifying the research problem in Pakistan (high maternal depression prevalence, literacy barriers, language barriers, limited mental health access, cultural stigma) to addressing six research gaps through the proposed AI system architecture (Roman Urdu interface, speech-to-text using Whisper, EPDS/PHQ-9 screening, NLP prediction, automated reports), culminating in improved maternal health outcomes (improved accessibility, early detection, reduced barriers, better maternal/child health). (Author's own illustration)

5. 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].
6. To implement crisis detection algorithms that identify keywords related to self-harm or suicide and trigger immediate safety protocols, ensuring user safety [47].
7. To implement automated report generation that provides easy-to-understand mental health insights and recommendations in Roman Urdu or simple English language [65].
8. To conduct comprehensive usability and user experience evaluation to assess the system's accessibility, acceptability, and satisfaction among low-literacy Pakistani mothers [40, 37].
9. To validate the accuracy and reliability of the AI-based mental health assessment in identifying women at risk due to biological, social, and psychological factors compared to standard clinical screening methods and establish clinical utility [64, 30].

1.7 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].

1.8 Scope and Limitations

1.8.1 Scope

This research encompasses the following elements:

Target Population: Pregnant women and postpartum mothers in Pakistan (up to 12 months post-birth), 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: Progressive Web Application (PWA) accessible via smartphones, tablets, and desktop computers, providing cross-platform compatibility without requiring app store downloads.

Core Functionalities:

- Mental health assessment using validated EPDS and PHQ-9 scales in conversational format
- Text and voice-based journal entries with sentiment and emotional analysis
- Biological risk profiling based on self-reported obstetric history and nutritional status
- Machine learning-based risk prediction and mental health status assessment
- Crisis detection and immediate safety protocol activation
- Automated report generation with easy-to-understand actionable insights and audio summaries in Roman Urdu
- Roman Urdu and Simple English language support with Voice-First interaction

- User interface design optimized for low-literacy populations (high-contrast visuals, icon-based navigation)

Technologies Implemented:

- **Frontend:** React.js/Next.js for PWA development
- **Backend:** Python (FastAPI/Flask)
- **AI/ML:** OpenAI Whisper (Speech-to-Text), Custom NLP models for Roman Urdu Sentiment Analysis, Scikit-learn for Risk Classification
- **Database:** Secure cloud storage (e.g., Firebase/PostgreSQL) with encryption for sensitive health data

1.8.2 Safety and Ethical Scope

Given the critical nature of mental health, the system defines strict boundaries for AI intervention:

- **Crisis Handling:** The system includes a rule-based "Kill Switch" for the chatbot. If keywords indicating self-harm or suicide are detected, the AI ceases conversation and provides immediate emergency contact numbers (e.g., Umang Pakistan, Rescue 1122).
- **Data Privacy:** To protect users in joint family systems, the application supports an "Incognito Mode" where voice journals are analyzed for sentiment and then discarded or encrypted, ensuring no text history remains on the device.

1.8.3 Limitations

While the proposed system addresses critical gaps, it is subject to the following limitations:

Methodological Limitations:

- **Self-Reporting Bias:** The accuracy of the biological risk profiling depends entirely on the user's honesty and memory regarding their medical history (e.g., nutritional intake, previous complications). The system cannot clinically verify these inputs.
- **Screening vs. Diagnosis:** The system is a screening tool based on standard scales (EPDS); it does not provide a clinical diagnosis, prescribe medication, or replace professional psychiatric care.

Technical Limitations:

- **Dialect Variation:** While the system supports Roman Urdu and English, accuracy may decrease with heavy regional accents (e.g., thick Punjabi or Pashto accents) or mixed-language code-switching that falls outside the training dataset.

- **Connectivity Dependence:** As a web-based AI solution, the system requires an active internet connection for speech processing, limiting accessibility in remote areas with poor connectivity.

  Sample Limitations:

- The prototype evaluation is limited to a specific sample size of women in urban/semi-urban Lahore and may not fully reflect the cultural nuances of deep rural tribal areas.

1.9 Thesis Organization

The remainder of this project documentation is organized as follows:

Chapter 2 (Literature Review): Provides a critical analysis of existing maternal mental health interventions, discusses the medical risk factors (hormonal, social) in depth, and presents a comparative analysis of existing AI tools to highlight the research gap.

Chapter 3 (Methodology): Details the system architecture, the conceptual framework integrating biological and social inputs, the data collection process, and the specific machine learning algorithms used for Roman Urdu processing.

Chapter 4 (Results and Discussion): Presents the implementation details, interface screenshots, usability testing results, and the performance metrics of the AI models.

Chapter 5 (Conclusion and Future Work): Summarizes the research findings, discusses the implications for public health in Pakistan, and outlines future enhancements such as integration with hospital EMR systems.

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.

2.10 Technological Interventions for High-Risk Pregnancies

While general mental health apps focus on Cognitive Behavioral Therapy (CBT), a distinct subset of literature explores digital interventions for medically high-risk pregnancies. Research indicates that women with complications such as gestational diabetes and preeclampsia exhibit anxiety levels significantly higher than the general pregnant population [54].

2.10.1 Digital Monitoring of Physiological Risk Factors

Current mobile health (mHealth) solutions for high-risk pregnancies typically focus on physiological tracking (e.g., blood glucose logging, blood pressure monitoring). A 2023 study on digital interventions for preeclampsia demonstrated that remote monitoring reduced maternal anxiety by providing a sense of control [88]. However, a critical gap remains: these physiological trackers rarely integrate *psychological* screening. Consequently, a mother tracking her high blood pressure may be spiraling into depression, but the app only records her BP readings. This necessitates a system that correlates biological inputs with mental health outputs.

2.10.2 Nutritional Psychiatry in Digital Health

Emerging research in "Nutritional Psychiatry" suggests that dietary tracking can be a preventative measure for depression. Apps that encourage the intake of micronutrients (Iron, Vitamin D, Omega-3) have shown promise in improving maternal mood [89]. However, existing nutrition apps in Pakistan are largely western-centric (counting calories rather than nutrients) and lack local dietary context (e.g., counting *roti* or *daal*), rendering them less effective for the target demographic.

2.11 Privacy-Preserving Technologies in Collective Cultures

In collectivist societies like Pakistan, the privacy of digital health interventions is paramount. The "Joint Family System" creates a unique threat model where shared devices and lack of physical privacy deter women from seeking help [5].

2.11.1 *The Failure of Text-Based Privacy*

Traditional mental health apps rely on text-based chat logs. Literature suggests that in shared-device households, the persistence of text history acts as a barrier to honest self-disclosure [42]. Women fear that husbands or in-laws may read their journals.

2.11.2 *Voice and Ephemeral Interfaces*

To counter this, recent Human-Computer Interaction (HCI) research proposes "Ephemeral Interfaces"—systems where data disappears after interaction. Voice-based interfaces offer a distinct privacy advantage: they leave no visual footprint on the screen. Furthermore, "Incognito Mode" features in health apps, which disguise the application as a utility (e.g., a calculator or calendar), have been effective in protecting users from domestic surveillance [90].

2.12 Comparative Analysis of Existing Solutions

To contextualize the proposed system, a comparative analysis of existing digital mental health interventions was conducted. Table 2.1 highlights the gaps in current solutions regarding language support, input modality, and cultural adaptability for the Pakistani context.

Table 2.1: Comparative Analysis of Mental Health Digital Interventions

System	**Language**	**Input**	**AI/ML**	**Target Users**	**Cultural Features**	**Limitations**
Wysa	English	Text	Yes	Western users	CBT-based	No Urdu; literacy required
Woebot	English	Text	Yes	Western users	CBT-based	No Urdu; literacy required
Taskeen	Urdu/Eng	Text	No	Pakistani public	Basic	Info only; no screening
Sehat Kahani	Urdu/Eng	Video	No	Patients	Pakistani	Costly; not scalable
ChatGPT	Multi	Text	Yes (LLM)	General	Generic	No validation; hallucinates
Proposed	**R-Urdu**	**Voice+Text**	**Yes (ML)**	**Low-literacy mothers**	**EPDS, PHQ-9, cultural**	**Prototype phase**

This comparison demonstrates that while effective solutions exist, none simultaneously address the *linguistic barrier* (Roman Urdu), the *literacy barrier* (Voice input), and the *specific biological/social domain* of maternal health in Pakistan.

2.13 Synthesis and Identification of Research Gaps

A critical review of the literature reveals that while significant progress has been made in isolated domains—maternal health screening, speech recognition, and AI chatbots—there is a notable absence of integrated solutions for the Global South.

The Primary Gap: No existing system combines **Roman Urdu Speech Recognition** with **Maternal Risk Profiling**. Current AI models are trained on high-resource languages, failing to capture the code-switching nuances of Pakistani speakers. **The Secondary Gap:** Existing platforms do not account for the "Double Burden" of biological risk (e.g., preeclampsia) and social risk (e.g., joint family stress) in their prediction logic.

Therefore, this research aims to fill these gaps by developing a multimodal, privacy-centric, and culturally aware AI monitoring system.

Chapter 3
METHODOLOGY

3.1 Overview

This chapter presents a comprehensive methodological framework for analyzing maternal mental health risks through multimodal data fusion and explainable artificial intelligence (XAI). The study integrates three complementary datasets to capture the multifaceted nature of maternal mental health: emotional self-reports, physiological biomarkers, and longitudinal behavioral patterns. This multi-pronged approach aligns with contemporary research emphasizing that maternal mental health requires integration of psychological, physiological, and temporal dimensions [?, ?].

The methodology is structured around six core phases: (1) dataset acquisition and characterization, (2) comprehensive preprocessing and quality assurance, (3) advanced feature engineering, (4) class imbalance mitigation, (5) model selection and training, and (6) explainable AI implementation.

3.2 Research Design and Philosophical Approach

3.2.1 Methodological Paradigm

This research adopts a positivist quantitative approach with an emphasis on predictive modeling rather than causal inference. The study employs supervised machine learning to identify patterns and risk factors associated with maternal mental health deterioration [?].

3.2.2 Ethical Considerations

All datasets used in this study are publicly available and anonymized. The research follows the TRIPOD (Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis) guidelines [?] and the MINIMAR (MINimum Information for Medical AI Reporting) framework [?].

Key Ethical Commitments:

- **Transparency:** All preprocessing steps, model architectures, and evaluation metrics are fully documented

- **Fairness:** Models are evaluated for potential demographic biases
- **Explainability:** SHAP values provide clinically interpretable explanations
- **Privacy:** No personally identifiable information (PII) is used or generated

3.3 Dataset Description and Rationale

The selection of three distinct datasets reflects the biopsychosocial model of maternal mental health, which recognizes that mental health outcomes result from biological, psychological, and social factors operating in concert [?]. Table 3.1 provides an overview of the three datasets used.

Table 3.1: Overview of Datasets Used in the Study

Dataset	Type	Primary Focus	Key Variables
Postnatal Emotional Health	Cross-sectional	Emotional symptoms	Depression symptoms, bonding, anxiety
Maternal Health Risk	Cross-sectional	Physiological biomarkers	Blood pressure, heart rate, blood sugar
14-Day PHQ-9 Tracking	Longitudinal	Temporal patterns	Daily depression scores, mood tracking

3.3.1 Dataset 1: Postnatal Emotional Health Dataset

Source and Context: This dataset contains self-reported emotional and behavioral symptoms from postpartum women during the critical 0-12 month postpartum period, when postpartum depression (PPD) prevalence peaks at 10-20% globally [?].

Core Variables:

- **Demographic:** Age, Age_Numeric
- **Emotional Symptoms:** Feeling sad or Tearful, Irritable towards baby & partner, Feeling anxious, Feeling of guilt
- **Behavioral Symptoms:** Trouble sleeping at night, Overeating or loss of appetite
- **Cognitive Symptoms:** Problems concentrating or making decision
- **Bonding:** Problems of bonding with baby
- **Critical Risk:** Suicide attempt
- **Temporal:** Hour, DayOfWeek

Engineered Features:

- `depression_risk_score`: Sum of all positive symptom endorsements

- `risk_level`: Three-tier classification (Low: 0-3, Moderate: 4-6, High: 7+)
- `sadness_bonding_interaction`: Interaction between sadness and bonding issues
- `anxiety_irritability_interaction`: Co-occurrence of anxiety and irritability
- `emotional_symptoms`, `behavioral_symptoms`, `cognitive_symptoms`: Symptom groupings

3.3.2 Dataset 2: Maternal Health Risk Dataset

Source and Context: This dataset contains clinical physiological measurements from pregnant women, collected during prenatal care visits [**?**].

Core Physiological Variables:

- **Cardiovascular:** SystolicBP, DiastolicBP, HeartRate
- **Metabolic:** BS (Blood Sugar), BodyTemp
- **Demographic:** Age
- **Target:** RiskLevel (Low, Medium, High)

Derived Features:

- `PulsePressure` = SystolicBP - DiastolicBP
- `MeanArterialPressure` = DiastolicBP + (PulsePressure / 3)
- `CardiovascularRisk`: Binary flag for hypertension or tachycardia
- `MetabolicRisk`: Binary flag for dysglycemia
- `MultiSystemRisk`: Both cardiovascular and metabolic risk present

Clinical Significance: Physiological dysregulation serves as an objective biomarker complementing subjective emotional reports, grounded in psychoneuroimmunology and allostatic load theory [**?**].

3.3.3 Dataset 3: 14-Day PHQ-9 Depression Tracking Dataset

Source and Context: This longitudinal dataset employs the Patient Health Questionnaire-9 (PHQ-9), the most widely validated depression screening tool [**?**]. Daily tracking over 14 days allows detection of temporal patterns invisible in cross-sectional data.

PHQ-9 Structure: Each of the 9 items corresponds to DSM-5 criteria for Major Depressive Disorder, scored 0-3:

- `phq1`: Anhedonia (little interest or pleasure)

- `phq2`: Depressed mood
- `phq3`: Sleep disturbance
- `phq4`: Fatigue
- `phq5`: Appetite change
- `phq6`: Guilt/worthlessness
- `phq7`: Concentration problems
- `phq8`: Psychomotor changes
- `phq9`: Suicidal ideation

Composite Scores:

- `phq9_total_score`: Sum of all 9 items (0-27)
- `core_depression_symptoms`: phq1 + phq2
- `somatic_symptoms`: phq3 + phq4 + phq5 + phq8
- `cognitive_symptoms`: phq6 + phq7

Clinical Cutoffs [?]:

- 0-4: Minimal/None
- 5-9: Mild depression
- 10-14: Moderate depression
- 15-19: Moderately severe depression
- 20-27: Severe depression

Temporal Features:

- `hour`, `day_of_week`, `is_weekend`: Time-of-day patterns
- `study_day`, `study_week`: Progression tracking
- `happiness_score`: Parallel positive affect measurement (0-10)

3.4 Data Preprocessing Pipeline

Figure 3.1 illustrates the complete preprocessing workflow.

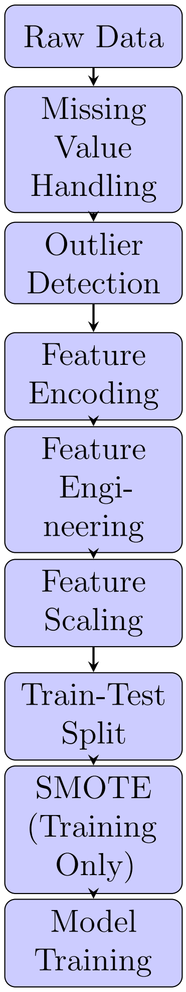

Figure 3.1: Data Preprocessing Pipeline

3.4.1 Missing Data Analysis and Imputation

Missing data mechanisms were analyzed following Rubin's framework [?]:

- **MCAR (Missing Completely At Random):** Missingness unrelated to any data
- **MAR (Missing At Random):** Missingness depends on observed data only
- **MNAR (Missing Not At Random):** Missingness depends on unobserved value itself

Imputation Strategies:

3.4.2 Outlier Detection and Treatment

Two complementary methods were employed:

1. IQR Method (Physiological Data):

$$\text{Lower Bound} = Q_1 - 1.5 \times IQR \tag{3.1}$$

Table 3.2: Imputation Methods by Variable Type

Variable Type	Method	Rationale
Numerical (physiological)	Median	Robust to outliers in clinical data
Categorical (symptoms)	Mode	Preserves population base rates
Suicide risk	Three-category	Distinguishes non-response from negative response
Time series (PHQ-9)	Forward/Backward Fill	Assumes gradual symptom changes

$$\text{Upper Bound} = Q_3 + 1.5 \times IQR \tag{3.2}$$

Outliers were capped (not removed) to preserve information about extreme values while preventing model distortion [**?**].

2. Z-Score Method (Psychometric Data):

$$Z = \frac{X - \mu}{\sigma} \tag{3.3}$$

Values with $|Z| > 3$ were flagged and reviewed for clinical plausibility.

3.4.3 Feature Encoding

- **Binary Symptoms:** Yes = 1, No = 0, Sometimes = 0.5
- **Nominal Categories:** One-hot encoding with k-1 dummy variables
- **Ordinal Target:** RiskLevel encoded as Low = 0, Moderate = 1, High = 2

3.4.4 Feature Scaling

Two scaling methods were applied based on variable characteristics:

Min-Max Scaling (Physiological variables):

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3.4}$$

Standardization (Psychometric variables):

$$X_{standardized} = \frac{X - \mu}{\sigma} \tag{3.5}$$

3.4.5 Advanced Feature Engineering

Feature engineering categories are summarized in Table 3.3.

Table 3.3: Engineered Feature Categories

Category	Examples	Clinical Rationale
Physiological Interactions	Age_BP_Interaction, BS_Age_Interaction	Compounded risk factors
Psychological Interactions	sadness_bonding_interaction, anxiety_irritability_interaction	High-risk phenotype identification
Temporal Patterns	late_night_response, weekend_response	Circadian and social patterns
Symptom Aggregations	emotional_symptoms, somatic_symptoms	Symptom cluster analysis

3.5 Handling Class Imbalance

3.5.1 The Imbalance Problem

Class distribution typically exhibits severe imbalance:

- Low Risk: 65-70%
- Moderate Risk: 20-25%
- High Risk: 8-12% (minority class)

Clinical Consequence: High false negative rate leads to missing high-risk mothers requiring urgent care.

3.5.2 SMOTE (Synthetic Minority Over-sampling Technique)

SMOTE generates synthetic samples for minority classes by interpolating between existing samples [?]:

$$x_{synthetic} = x + \lambda \times (x_{neighbor} - x) \tag{3.6}$$

where $\lambda \sim \text{Uniform}(0, 1)$ and $x_{neighbor}$ is one of k-nearest neighbors (k=5).

Critical Protocol: SMOTE applied ONLY to training data to prevent data leakage and maintain realistic test set distribution.

Listing 3.1: SMOTE Implementation

```
from imblearn.over_sampling import SMOTE

smote = SMOTE(sampling_strategy='auto',
                  k_neighbors=5,
                  random_state=42)
X_train_balanced, y_train_balanced = smote.fit_resample(
    X_train, y_train)
```

3.6 Train-Test Split and Cross-Validation

3.6.1 Data Partitioning

Selected Split: 80% Training / 20% Testing with stratified sampling to preserve class distribution [?].

Listing 3.2: Stratified Train-Test Split

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42)
```

3.6.2 Cross-Validation Strategy

Method: 5-Fold Stratified Cross-Validation

- Divides training data into 5 equal folds
- Each fold maintains original class distribution
- Training repeated 5 times, each with different validation fold
- Performance metrics averaged across folds

For Temporal Data (PHQ-9): Time-Series Cross-Validation to prevent data leakage:

Listing 3.3: Time Series Cross-Validation

```
from sklearn.model_selection import TimeSeriesSplit

tscv = TimeSeriesSplit(n_splits=5)
for train_idx, val_idx in tscv.split(X):
    # Train on past, validate on future
    X_train, X_val = X[train_idx], X[val_idx]
```

3.7 Model Selection and Architecture

Four machine learning algorithms were selected based on complementary strengths (Table 3.4).

Table 3.4: Model Selection Rationale

Model	Primary Strength	Best For	Limitation
Logistic Regression	Interpretability	Baseline, linear relationships	Poor with non-linearity
Random Forest	Handles non-linearity	Noisy survey data	Black box
SVM	High-dimensional data	PHQ-9 features	Computationally expensive
XGBoost	State-of-art performance	Physiological data	Hyperparameter sensitive

3.7.1 Logistic Regression

Mathematical Formulation:

$$P(y = 1|X) = \frac{1}{1 + e^{-(\beta_0+\beta_1 x_1+...+\beta_n x_n)}} \tag{3.7}$$

Hyperparameters:

- penalty='l2' (Ridge regularization)
- C=1.0 (inverse regularization strength)
- solver='lbfgs'
- multi_class='multinomial'
- class_weight='balanced'

3.7.2 Random Forest Classifier

Ensemble of decision trees trained on random subsets with feature randomness [**?**].

Key Hyperparameters:

- n_estimators=200 (number of trees)
- max_depth=10 (prevents overfitting)
- min_samples_split=4
- max_features='sqrt'
- class_weight='balanced'

Feature Importance: Computed via Mean Decrease in Impurity (Gini Importance).

3.7.3 Support Vector Machine (SVM)

Finds hyperplane that maximally separates classes in high-dimensional space [?].

Kernel: Radial Basis Function (RBF)

$$K(x_i, x_j) = \exp(-\gamma||x_i - x_j||^2) \tag{3.8}$$

Hyperparameters:

- kernel='rbf'
- C=1.0 (regularization)
- gamma='scale' (kernel coefficient)
- class_weight='balanced'
- probability=True

3.7.4 XGBoost (Extreme Gradient Boosting)

Sequential ensemble where each tree corrects previous trees' errors [?].

Key Hyperparameters:

- objective='multi:softprob'
- learning_rate=0.05
- n_estimators=300
- max_depth=6
- subsample=0.8
- colsample_bytree=0.8
- scale_pos_weight (for imbalance)

Early Stopping: Training stops if validation loss doesn't improve for 50 rounds.

3.8 Model Explainability with SHAP

3.8.1 The Black Box Problem

Complex models require explanation mechanisms to be clinically acceptable. SHAP (SHapley Additive exPlanations) provides model-agnostic interpretability [?].

3.8.2 SHAP Methodology

Based on Shapley values from game theory, SHAP values satisfy:

$$\text{Prediction} = \text{Base Value} + \sum_{i=1}^{m} \phi_i \tag{3.9}$$

where ϕ_i is the contribution of feature i.

Interpretation:

- $\phi_i > 0$: Feature pushes prediction higher (increases risk)
- $\phi_i < 0$: Feature pushes prediction lower (decreases risk)
- $|\phi_i|$: Magnitude of impact

3.8.3 SHAP Visualizations

Four primary visualization types were used:

1. **Waterfall Plot:** Individual prediction explanation
2. **Summary Plot (Bar):** Global feature importance ranking
3. **Beeswarm Plot:** Feature impact distribution
4. **Dependence Plot:** Feature interaction effects

Listing 3.4: SHAP Implementation

```python
import shap

# Create explainer
explainer = shap.TreeExplainer(model)

# Calculate SHAP values
shap_values = explainer.shap_values(X_test)

# Visualize
shap.summary_plot(shap_values, X_test)
```

3.9 Evaluation Metrics

Medical AI requires domain-appropriate metrics aligned with clinical priorities. Table 3.5 summarizes the evaluation framework.

Table 3.5: Evaluation Metrics and Clinical Significance

Metric	Formula	Clinical Importance	Target
Recall	$\frac{TP}{TP+FN}$	Catch high-risk mothers	$\geq 80\%$
Precision	$\frac{TP}{TP+FP}$	Minimize false alarms	$\geq 60\%$
F1-Score	$\frac{2\times P\times R}{P+R}$	Balance recall/precision	≥ 0.68
ROC-AUC	Area under ROC curve	Ranking ability	≥ 0.85

3.9.1 Primary Metric: Recall (Sensitivity)

Definition:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3.10}$$

Clinical Rationale: False negatives are dangerous—missing a depressed mother can lead to suicide or child neglect. High recall ensures most high-risk mothers are identified.

3.9.2 Confusion Matrix Analysis

For 3-class classification, critical cells are:

- **Bottom-Left (High→Low):** Most dangerous misclassification
- **Top-Right (Low→High):** Acceptable over-referral
- **Diagonal:** Correct predictions

Normalized confusion matrices display percentages for interpretability.

3.10 Experimental Setup

3.10.1 Hardware and Software

Hardware:

- CPU: Intel Core i7 / AMD Ryzen 7 (8 cores)
- RAM: 16 GB DDR4
- Storage: 500 GB NVMe SSD

Software Environment:

- Python 3.10.12
- scikit-learn 1.3.0
- xgboost 1.7.6
- imbalanced-learn 0.11.0

- shap 0.42.1
- pandas 2.0.3, numpy 1.24.3

3.10.2 Reproducibility Measures

- Fixed random seeds (random.seed(42), np.random.seed(42))
- Version-controlled code (Git)
- Exact library versions specified in requirements.txt

3.11 Validation Strategy

Multi-tiered validation approach:

1. **Internal Validation:** 5-fold stratified cross-validation
2. **Temporal Validation:** Time-series split for PHQ-9 dataset
3. **Hold-Out Test Set:** 20% unseen data for final evaluation
4. **SHAP-Based Clinical Validation:** Verify feature importance aligns with literature
5. **Fairness Validation:** Check performance across demographic subgroups

3.12 Ethical Considerations

3.12.1 Algorithmic Fairness

Models evaluated for demographic parity and equal opportunity across age groups:

Listing 3.5: Fairness Auditing

```
for age_group in ['<25', '25-35', '>35']:
    subset = test_data[test_data['age_group'] == age_group]
    recall = recall_score(subset['y_true'],
                          subset['y_pred'],
                          average='macro')
    print(f"Recall for {age_group}: {recall:.3f}")
```

3.12.2 Clinical Deployment Workflow

Recommended integration:

1. Patient completes questionnaire + vitals recorded

2. Model generates risk score
3. High Risk (≥ 0.7): Immediate psychiatrist referral
4. Moderate Risk (0.4-0.7): Follow-up screening in 2 weeks
5. Low Risk (¡0.4): Standard care
6. **All flagged cases reviewed by human clinician**

3.13 Limitations

1. **Cross-Sectional Design:** Two datasets cannot establish causality
2. **Self-Report Bias:** Social desirability may lead to underreporting
3. **Geographic Specificity:** Physiological dataset from Bangladesh may limit generalizability
4. **Missing Socioeconomic Variables:** No data on income, education, social support
5. **Model Interpretability Trade-offs:** Complex models less transparent than logistic regression despite SHAP explanations

3.14 Summary

This chapter presented a rigorous methodological framework integrating three complementary datasets through advanced preprocessing, feature engineering, and machine learning techniques. The emphasis on explainability via SHAP and careful attention to class imbalance ensures the developed models are both accurate and clinically interpretable. The next chapter presents the results of applying this methodology.

Chapter 4
RESULTS AND DISCUSSION

4.1 Model Training and Validation

4.2 Performance Comparison

4.3 Visualizations

4.4 Discussion of Results

4.4.1 Strengths

4.4.2 Weaknesses

4.4.3 Unexpected Findings

Chapter 5
CONCLUSION AND FUTURE WORK

5.1 Summary of Findings

5.2 Contributions of the Study

5.3 Limitations

5.4 Suggestions for Future Research

5.5 Concluding Remarks

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