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A Software Engineering Framework for Designing, Governing, and Deploying AI-Driven, Culturally Adaptive Systems: A Mental Health Case Study in Bangladesh

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Attestation

I hereby declare that the thesis entitled *"A Software Engineering Framework for Designing, Governing, and Deploying AI-Driven, Culturally Adaptive Systems: A Mental Health Case Study in Bangladesh"* has been carried out and written by me under the supervision of **Asif Mahmood, PhD**, Assistant Professor, Department of Computer Science and Engineering, Independent University, Bangladesh, for the partial fulfillment of the requirements for the degree of Master of Science in Software Engineering.
I affirm that this work is original, has not been submitted previously for any academic award, and all sources and contributions have been duly acknowledged.

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. . . . . .

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Abstract

Mental health disorders represent a critical and growing public-health challenge in Bangladesh, yet access to affordable, culturally appropriate, and trustworthy psychological support remains severely limited. Empirical findings based on the DASS-21 instrument demonstrate significant levels of depression, anxiety, and stress among Bangladeshi populations, while existing services are constrained by shortages of professionals, linguistic barriers, stigma, and fragmented digital infrastructure. This thesis addresses this gap by proposing a bilingual, culturally adaptive, AI-assisted mental-health screening system designed specifically for low-resource environments.

The research adopts a multidisciplinary software-engineering perspective, arguing that the success of AI in mental healthcare depends not only on model accuracy but also on governance, development process, architecture, quality assurance, and deployment economics. To operationalize this vision, the study introduces the SAEAF (Software Architecture Economics Alignment Framework), a modular architecture that integrates Human-Centered AI principles with ethical safeguards, explainable recommendations, and Bangla-English interaction. The work further evaluates how Agile Governance and Hybrid Project Management can manage the complexity of interdisciplinary AI healthcare projects, ensuring traceable requirements, regulatory alignment, and stakeholder trust.

A comprehensive analysis of AI-based software testing demonstrates its role in maintaining safety and reliability in multilingual, continuously evolving systems, while an assessment of Cloud IaaS deployment establishes the economic feasibility and scalability required for nationwide adoption. Synthesizing these dimensions, the thesis shows that sustainable impact emerges from the integration of governance, architecture, intelligent testing, and cloud economics rather than from AI algorithms alone.

The findings contribute: (1) an empirically grounded justification for AI-driven mental-health screening in Bangladesh; (2) the SAEAF architectural model tailored to low-resource contexts; (3) a governance and hybrid delivery approach for ethical AI healthcare; and (4) an economic rationale for AI-based testing and cloud deployment. The research concludes that responsible software-engineering strategy is fundamental to transforming AI mental-health innovation into a practical, scalable, and socially trusted service.

Publication List

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1 Introduction

Mental health disorders have become a major public health concern worldwide, with developing nations experiencing disproportionate burdens due to limited healthcare infrastructure, social stigma, and shortages of trained professionals. Bangladesh reflects this global challenge acutely, where depression, anxiety, and stress are increasingly observed among students, young professionals, and vulnerable communities [1]. Although digital technologies and artificial intelligence offer promising opportunities for expanding access to early screening and support, deploying such systems in low-resource and culturally diverse environments introduces significant ethical, technical, and software engineering challenges.

This thesis proposes a human-centered, bilingual AI-enabled mental health screening approach grounded in the Depression Anxiety Stress Scales – 21 (DASS-21) framework and structured through the Software Architecture–Economic Alignment Framework (SAEAF). The goal is to design a system that is not only technically robust but also culturally appropriate, ethically governed, and operationally feasible for the Bangladeshi context. The following sections first describe the mental health challenges in Bangladesh, then discuss the opportunities and constraints associated with AI-based screening technologies, followed by the software engineering challenges involved in developing such systems. These discussions ultimately lead to the research questions, objectives, and contributions of this study.

1.1 Mental Health Challenges in Bangladesh

Bangladesh faces a significant mental health treatment gap driven by social, economic, and infrastructural constraints. Access to psychiatrists and psychologists is largely concentrated in major cities, while a large proportion of the population resides in semi-urban and rural regions. Social stigma surrounding mental illness further discourages individuals from seeking professional help, and psychological distress is often interpreted through cultural or non-clinical perspectives [1].

Recent national studies indicate a growing prevalence of depression and anxiety among university students, garment industry workers, and urban youth populations. The COVID-19 pandemic intensified psychological vulnerability, yet structured mental health screening services remain limited outside major healthcare facilities. Many existing psychological assessment tools are designed for clinical environments, are predominantly English-based, and require trained administrators, which restricts their accessibility and usability for the broader population [2].

These conditions highlight the need for accessible, culturally appropriate mental health screening mechanisms that can operate outside traditional clinical envi-

ronments. Digital platforms capable of supporting self-administered assessments in local languages could significantly improve early identification and awareness of mental health risks.

While the need for accessible mental health support is increasingly evident, traditional healthcare systems alone cannot address the growing demand. Digital technologies, particularly artificial intelligence, have emerged as potential tools for expanding the reach of mental health screening and early detection services. However, the application of such technologies must carefully consider cultural, linguistic, and ethical realities specific to Bangladesh.

1.2 AI Potential with Ethical and Cultural Constraints

Artificial intelligence (AI) has the potential to transform digital mental health systems by enabling automated screening, conversational interfaces, and personalized guidance at a scale that traditional services cannot easily achieve. AI models can analyze responses to validated psychological instruments such as the DASS-21, identify potential patterns of depression, anxiety, or stress, and provide preliminary feedback or recommendations to users. Recent studies highlight that AI-based mental health tools can assist in early detection and improve accessibility to mental health services, particularly in regions with limited clinical resources [3], [4], [5].

However, the adoption of AI in mental health contexts also raises several important concerns. AI models trained primarily on Western datasets may fail to capture culturally specific expressions of emotional distress, while limitations in Bengali natural language processing (NLP) further constrain system accuracy and usability. In addition, ethical issues related to data privacy, informed consent, algorithmic bias, and potential misclassification risks must be carefully managed in healthcare applications [1], [3]. These challenges are compounded by issues of trust and transparency, as users may be reluctant to rely on automated mental health assessments without clear explanations of how recommendations are generated [4].

These considerations indicate that the successful deployment of AI-based mental health systems requires more than algorithmic accuracy. Effective solutions must incorporate human-centered design principles, cultural adaptability, and robust ethical governance mechanisms to ensure that technology supports—rather than replaces—responsible healthcare practices.

1.3 Software Engineering Challenges in AI Healthcare Systems

Developing AI-enabled healthcare systems involves complex software engineering considerations that extend beyond algorithm development. Prior research emphasizes that AI-driven healthcare applications require strong software engineering practices to ensure safety, reliability, and regulatory compliance [6], [7]. Mental health screening platforms must integrate validated psychometric instruments, en-

sure reliable system performance, maintain user privacy, and support deployment across diverse technological environments.

Several challenges arise when designing such systems:

- Integration of psychological assessment frameworks such as DASS-21 with AI-based analysis mechanisms.
- Continuous system validation as user populations, language usage, and cultural contexts evolve.
- Governance mechanisms to ensure ethical compliance and responsible use of AI technologies.
- Scalable system architectures capable of operating in resource-constrained environments.
- Quality assurance processes that address both traditional software risks and AI-specific uncertainties.
- Deployment strategies that maintain accessibility, reliability, and operational efficiency.

Traditional software development approaches are often insufficient for addressing these challenges, as AI-based systems evolve dynamically with data and user interactions. Emerging research suggests that integrating governance frameworks, hybrid project management approaches, and architecture-driven development strategies can improve the reliability and sustainability of complex AI systems [6], [8], [9].

To address these interconnected challenges, this research adopts an integrated software engineering strategy that combines human-centered AI principles with structured development and governance mechanisms. The proposed approach brings together Agile governance, hybrid project management, architecture-driven alignment, and AI-aware quality assurance practices to ensure that the resulting mental health screening system remains reliable, scalable, ethically responsible, and suitable for deployment in low-resource environments.

1.4 Research Motivation

Mental health screening in Bangladesh faces multiple structural and contextual barriers that limit access to timely support. These challenges include the limited availability of mental health professionals, the concentration of services in major urban centers, persistent social stigma surrounding mental illness, and the linguistic inaccessibility of many digital mental health platforms. In addition, economic constraints and infrastructural limitations further restrict the deployment of scalable digital healthcare systems across the country.

Although recent advances in artificial intelligence and digital health technologies offer promising opportunities for improving mental health accessibility, many existing systems fail to adequately address the socio-cultural and operational realities of low-resource environments. In particular, current digital mental health

platforms often lack culturally adaptive interfaces, governance-aware development practices, and architectural designs that align technical decisions with economic sustainability.

Furthermore, the development of AI-enabled healthcare systems introduces additional software engineering challenges related to system governance, architectural scalability, quality assurance, and cloud-based deployment. These factors are rarely addressed in an integrated manner within existing research.

Therefore, this research is motivated by the need to develop a structured and sustainable software engineering approach for AI-driven mental health screening systems. By integrating human-centered AI principles, hybrid project management practices, architecture–economic alignment through the SAEAF framework, AI-assisted testing strategies, and scalable cloud deployment models, this study aims to address both the technical and contextual challenges associated with digital mental health systems in Bangladesh.

1.5 Research Questions

To systematically address the central problem of developing a culturally adaptive, ethically governed, and scalable AI-assisted mental health screening platform for Bangladesh, this study is guided by one overarching research question and three supporting sub-research questions.

Overarching Research Question (ORQ):

How can a human-centered, bilingual, AI-assisted mental health screening system be engineered and governed to ensure accessibility, cultural appropriateness, safety, and long-term sustainability in low-resource environments such as Bangladesh?

To answer this overarching question, the following sub-research questions are investigated:

- **RQ1 (System Design and Accessibility):** How can a bilingual, culturally adaptive DASS-21-based system be designed to support accessible mental health screening in Bangladesh?
- **RQ2 (Engineering Process and Governance):** What software engineering frameworks and governance processes are most effective for developing AI-driven healthcare applications in low-resource and culturally diverse environments?
- **RQ3 (Quality, Safety, and Scalability):** How can the quality, safety, and scalability of AI-based mental health screening systems be ensured through appropriate architecture design, testing strategies, and cloud deployment models?

1.6 Research Objectives

To address the overarching research question and its supporting sub-research questions, this study defines a set of objectives focused on the design, governance, and

deployment of AI-driven and culturally adaptive software systems for low-resource environments.

The primary objective of this research is to develop a software engineering framework for designing, governing, and deploying AI-driven, culturally adaptive mental health systems suitable for resource-constrained environments such as Bangladesh.

To achieve this objective, the research pursues the following specific objectives:

- To analyze the challenges associated with digital mental health systems in low-resource environments, particularly regarding accessibility, cultural adaptability, usability, governance, and deployment feasibility.
- To design and validate a bilingual and culturally adaptive mental health screening system based on the DASS-21 framework that supports both English and Bangla language users. (RQ1)
- To incorporate human-centered AI principles into the system design in order to improve usability, accessibility, trust, and user engagement in AI-supported healthcare applications. (RQ1)
- To develop the Unified Agile Governance Framework (UAGF) for managing and governing AI-driven and distributed software development environments through structured Agile governance and hybrid project management practices. (RQ2)
- To develop the Software Architecture–Economics Alignment Framework (SAEAF) for supporting architectural design, quality assurance, deployment planning, and economic evaluation of AI-enabled healthcare systems. (RQ2)
- To evaluate the proposed frameworks and system in terms of architectural feasibility, governance effectiveness, quality assurance capability, scalability, and operational sustainability within low-resource deployment contexts. (RQ3)

1.7 Research Contributions

This research contributes to the fields of software engineering, Agile governance, human-centered artificial intelligence, and digital mental health systems through the development and integration of two complementary frameworks: the Unified Agile Governance Framework (UAGF) and the Software Architecture–Economics Alignment Framework (SAEAF). These contributions collectively support the design, governance, testing, and deployment of AI-driven and culturally adaptive systems for low-resource environments.

The contributions of this thesis are mapped directly to the research objectives as follows:

- **Contribution 1 – Bilingual and Culturally Adaptive Mental Health System:**

  To address Objective 2, this research designs and validates a bilingual digital mental health screening system based on the validated DASS-21 instrument.

The system supports both English and Bangla language users while incorporating culturally adaptive interface and interaction considerations relevant to the Bangladeshi context.

- **Contribution 2 – Integration of Human-Centered AI Principles:**

  To address Objective 3, the research incorporates human-centered AI principles into the proposed system to improve usability, accessibility, trust, and user engagement. The work emphasizes inclusive interaction design and ethical AI-supported healthcare delivery for resource-constrained environments.

- **Contribution 3 – Unified Agile Governance Framework (UAGF):**

  To address Objective 4, this research proposes the Unified Agile Governance Framework (UAGF), a governance-oriented framework designed for AI-driven and distributed software development environments. UAGF integrates Agile practices with structured governance mechanisms to support coordination, accountability, ethical oversight, and hybrid project management in complex healthcare-oriented systems.

- **Contribution 4 – Software Architecture–Economics Alignment Framework (SAEAF):**

  To address Objective 5, this research develops the Software Architecture–Economics Alignment Framework (SAEAF), which aligns software architecture decisions with economic feasibility, quality assurance, scalability, deployment sustainability, and operational performance. The framework supports SMEs in evaluating AI-enabled healthcare systems within low-resource environments.

- **Contribution 5 – Integrated Evaluation of Governance, Architecture, Quality Assurance, and Deployment:**

  To address Objective 6, this research performs a multi-dimensional evaluation of the proposed system and frameworks from governance, architectural, quality assurance, deployment, and operational perspectives. The evaluation demonstrates the feasibility of integrating UAGF and SAEAF to support the sustainable development and deployment of AI-driven mental health systems in Bangladesh.

1.8 Organization of the Thesis

The remainder of this thesis is organized as follows.

Chapter 2 presents the literature review, examining existing research related to artificial intelligence in mental health systems, human-centered AI design, requirements engineering practices, Agile governance and hybrid project management, software architecture for AI systems in low-resource environments, quality assurance and AI-based testing, and cloud computing deployment strategies.

Chapter 3 describes the research methodology and conceptual framework adopted in this study. It explains the design principles guiding the development of the proposed system and introduces the SAEAF architectural framework used in the research.

Chapter 4 presents the design and implementation of the proposed bilingual mental health screening system based on the DASS-21 instrument and explains the core system components and operational workflow.

Chapter 5 discusses the software engineering strategies used during system development, including Agile governance practices and hybrid project management approaches.

Chapter 6 analyzes the architectural design of the system using the SAEAF framework and evaluates its economic and operational implications for deployment in low-resource environments.

Chapter 7 explores quality assurance considerations, including AI-based testing strategies and system validation approaches.

Chapter 8 presents the evaluation and discussion of the proposed system, synthesizing findings across governance, architecture, testing, and cloud deployment dimensions.

Finally, Chapter 9 concludes the thesis and outlines directions for future research.

2 Literature Review

This chapter reviews the existing literature relevant to AI-driven mental health systems, human-centered artificial intelligence, software engineering practices, and scalable deployment strategies. The objective of this chapter is to establish the theoretical and empirical foundation for the proposed research by identifying key advancements, limitations, and research gaps across multiple interrelated domains.

The chapter is organized as follows. Section 2.1 examines the application of artificial intelligence in mental health systems, with a focus on screening, prediction, and accessibility challenges. Section 2.2 explores Human-Centered AI and Requirements Engineering, emphasizing ethical, cultural, and user-centered considerations. Section 2.3 reviews Agile governance and hybrid project management approaches in distributed and AI-driven environments. Section 2.4 analyzes software architecture in low-resource contexts, particularly its relationship with economic sustainability. Section 2.5 discusses quality assurance and testing strategies for AI-based systems. Section 2.6 evaluates cloud computing as an enabling infrastructure for scalable AI healthcare applications. Finally, Section 2.7 synthesizes the findings and identifies key research gaps that motivate this study.

2.1 AI in Mental Health System

The application of AI and ML in mental health diagnosis and intervention has expanded rapidly in recent years, with studies demonstrating promising results in automated screening, prediction, and personalized support. Systematic reviews have shown that ML models applied to electronic health records can predict and diagnose depression with notable accuracy, although concerns regarding model generalizability and contextual validity remain prominent [10].

In the Bangladeshi context, several studies have applied ML techniques to mental health assessment using standardized instruments such as the DASS-21. Islam et al. demonstrated statistically significant relationships between anxiety and depression among university students; however, their reliance on English-language datasets limited cultural and linguistic applicability [1]. Subsequent work addressing this limitation introduced multilingual and Bangla-adapted versions of DASS-21, confirming reliability and validity across localized populations. Despite these advances, most studies focused primarily on predictive accuracy rather than user interaction, system integration, or deployment feasibility in real-world settings. [11], [12]

Globally, research has emphasized AI's potential to improve mental health care access in low-resource environments.Surveys by Rehman et al. and Osman et al. highlighted the suitability of AI-driven screening tools for underserved popu-

lations [7], [13], while earlier analysis in Bangladesh underscored AI's capacity to reduce the burden on limited mental health professionals [14]. Nevertheless, these systems largely remain experimental, with limited evidence of sustained adoption, scalability, or operational integration.

Conversational AI and chatbot-based interventions have emerged as popular modalities for mental health support. Studies evaluating systems such as Wysa, Tess, and similar agents reported positive initial user engagement and accessibility benefits [15], [16]. However, issues related to repetitive responses, declining long-term engagement, and lack of personalization were consistently identified [16], [17]. Comparative studies further demonstrated that domain-specific AI assistants outperform general-purpose large language models (LLMs) in healthcare contexts, particularly in terms of trust, relevance, and safety [18], [19]

Recent work has explored integrating LLMs into mental health services to enhance personalization and conversational flexibility [20], [21], [22], While these approaches show promise in depression detection and journaling-based interventions, researchers consistently caution against ethical risks, including bias, hallucinated outputs, privacy concerns, and insufficient clinical validation [4], [23].

These concerns are amplified in culturally diverse and digitally marginalized populations, where misinterpretation and mistrust may undermine system effectiveness. Beyond conventional mental health screening, AI tools have also been explored for adolescent-focused mobile interventions and personalized therapeutic applications such as AI-driven art therapy, demonstrating the expanding scope of AI in mental health [24], [25].

Ethical and cultural considerations remain central across the literature. Multiple studies stress the necessity of transparency, bias mitigation, and culturally informed design in AI-driven mental health systems [3], [4], [5]. In Bangladesh specifically, infrastructural limitations, digital literacy gaps, and ethical governance challenges continue to impede large-scale deployment [1]. The COVID-19 pandemic further highlighted the urgency of accessible mental health solutions, as elevated levels of anxiety and depression were reported among children, students, people with disabilities, and other vulnerable groups [2], [14], [26]

Taken together, these findings highlight that technical effectiveness alone is insufficient for the successful deployment of AI-driven mental health systems. Ethical integrity, cultural sensitivity, and user trust emerge as foundational requirements, particularly in low-resource contexts such as Bangladesh, where social, infrastructural, and governance constraints shape system adoption and long-term impact.

Addressing these challenges requires moving beyond post hoc ethical considerations toward design approaches that embed human values and contextual awareness from the earliest stages of system development. In this regard, Human-Centered Artificial Intelligence and requirements engineering provide critical frameworks for systematically translating ethical, cultural, and user-centered concerns into concrete system requirements and design decisions.

2.2 Human-Centered AI & Requirements Engineering

Human-Centered Artificial Intelligence (HCAI) emphasizes the design of AI systems that prioritize human values, usability, transparency, and ethical responsibility throughout the system lifecycle. In contrast to purely performance-driven AI models, HCAI integrates user needs, contextual constraints, and socio-cultural factors into system development, making it particularly relevant for healthcare and mental health applications.

Within software engineering, Requirements Engineering (RE) plays a critical role in translating human-centered principles into verifiable system specifications. Traditional RE approaches focus on functional and non-functional requirements such as performance, reliability, and security; however, AI-driven systems introduce additional complexity due to data dependency, model uncertainty, and adaptive behavior. Studies by Luxton et al. and Lee et al. highlight that ethical concerns—including bias, explainability, and privacy—must be treated as first-class requirements rather than post hoc considerations in AI healthcare systems [3], [23].

Recent research has explored incorporating human-centered design methodologies into requirements elicitation for AI applications. Ghosal et al. proposed an AI-informed experience-based co-design approach to capture user expectations and emotional needs during system design [27]. Similarly, Jelassi et al. emphasized the importance of integrating behavioral and linguistic cues into requirements for personalized mental health support platforms. While these approaches improve user alignment, they often lack formal validation mechanisms within established RE frameworks [28].

Cultural and linguistic adaptation is a particularly significant requirement for mental health systems deployed in low-resource environments. Studies validating localized versions of DASS-21 demonstrate that direct adoption of globally developed assessment tools may result in misinterpretation or reduced engagement if cultural nuances are ignored [12]. Ahmed et al. further noted that AI models trained on English-language datasets fail to adequately represent Bangladeshi populations, reinforcing the need for culturally adaptive requirements elicitation and validation processes [12]

Another challenge in HCAI-driven systems is stakeholder diversity. Mental health platforms must address the needs of patients, clinicians, caregivers, and policymakers, each with distinct expectations and constraints. Van Bussel et al. found that trust, transparency, and perceived usefulness significantly influence user acceptance of virtual assistants in healthcare. These findings underscore the importance of explicitly modeling trust and explainability as non-functional requirements within AI system specifications [18].

Despite growing recognition of HCAI principles, existing literature reveals a gap between conceptual guidelines and practical software engineering implementation. Many AI-based mental health systems document ethical intentions but fail to provide traceable requirements, validation criteria, or lifecycle governance mechanisms [7]. Furthermore, empirical evaluation of requirements effectiveness—such as pre- and post-deployment user studies—remains limited, particularly in

developing countries.

These limitations indicate that addressing ethical and human-centered requirements cannot be treated solely as a design-time concern. Instead, they necessitate continuous governance structures that ensure traceability, accountability, and adaptability throughout the software development lifecycle. In AI-driven mental health systems—particularly those developed by distributed teams—requirements evolve in response to user feedback, regulatory expectations, and ethical risk assessments.

Consequently, project management and governance approaches must support iterative validation, cross-functional collaboration, and decision-making transparency. Agile governance and hybrid project management frameworks offer mechanisms to bridge strategic ethical objectives with day-to-day development practices, making them especially relevant for managing AI-enabled systems in distributed and socio-technical contexts.

2.3 Agile Governance and Hybrid Project Management in AI-Driven and Distributed Teams

Agile governance in AI-driven and distributed project environments has emerged as a critical area of research due to increasing system complexity, geographical dispersion of teams, and the integration of AI components that introduce ethical, technical, and operational uncertainties. Existing literature highlights the need to balance flexibility with structured oversight, particularly in large-scale and socio-technical systems.

This section reviews prior research across three key dimensions: (i) Agile adaptation in distributed environments, (ii) team dynamics and psychological safety, and (iii) the alignment of Agile methodologies with governance frameworks. It further examines the evolution of hybrid project management approaches designed to address the limitations of purely Agile or plan-driven models.

2.3.1 Agile Adaptation in Distributed Environments

Hooper et al. examined how Agile teams adapt practices and skills when working remotely. They used SAFe case studies from the finance sector. The study shows that structured virtual communication and clear accountability help preserve Agile values when rituals are disrupted [29].

Cai et al. analyzed Agile project management in virtual teams. They found common problems such as communication breakdowns, time zone barriers, and gaps in leadership. The authors recommended structured communication plans, adapted ceremonies, and effective digital collaboration tools [30]

Masili et al. studied social and technical factors in distributed Agile teams. They identified issues such as loss of trust, poor coordination, and hard onboarding. Their solution is to balance digital tools and rituals with trust and shared leadership through hybrid work and flexible governance [31].

2.3.2 Team Dynamics, Psychological Safety, and Communication

Matharu et al. investigate psychological safety in hybrid software teams. They find that reduced spontaneous interaction limits open dialogue and feedback. Aligned hybrid schedules and deliberate rituals help restore safety [32].

Ahmad et al. emphasize psychological safety and relationship quality as enablers of team learning and performance in large scale Agile. Survey results from 167 professionals show that open dialogue and shared goals improve delivery outcomes [33].

Ng et al. addresses falling engagement in remote retrospectives. They showed that gamification, anonymous feedback, and continuous documentation raise participation and encourage proactive problem solving [34].

Moustafa identifies 23 critical success factors across team environment, communication, and management. He highlights self-organization, feedback, and training as foundations for success in distributed Agile [35].

2.3.3 Frameworks, Methods, and Governance Alignment

Matharu et al. compares six Agile methods, including Scrum, XP, FDD, DSDM, ASD, and Kanban. They link each method's effectiveness to project size, complexity, and communication patterns. These findings support adaptive governance that aligns method and context [32].

David et al. uses sentiment-based text mining to study how Agile aligns with PMBOK areas. They reported harmony in scope and stakeholder management but tension in integration and procurement. Governance must reconcile these tensions [36].

Ranner et al. studied large-scale Agile coordination. They found that as autonomy grows, teams move from scheduled meetings to informal interaction, which calls for coordination that is both structured and flexible [37].

Maganova et al. explored cross-organizational Agile setups. They report misaligned maturity, unclear roles, and weak change support. The study suggests governance that bridges silos and supports cohesion [38].

Virag et al. identified four Agile management styles: Landscaper, Buddy, Detective, and Commander. These styles show how managers balance control and autonomy to keep trust and flexibility in distributed projects [39].

Camara et al. reviewed 74 studies and list 96 tailored Agile practices. They argued that contingency factors and method engineering are essential for scaling Agile across diverse contexts [40].

2.3.4 Hybrid Project Management for Complex and Large-Scale Systems

Large-scale and complex software systems face dual challenges: the need for adaptability to evolving requirements and the need for structured governance to ensure risk mitigation, compliance, and stakeholder alignment. Traditional plan-driven methodologies provide strong managerial control but often lack responsiveness to

rapidly changing requirements. In contrast, Agile approaches emphasize flexibility and iterative development but may struggle to provide adequate oversight in distributed or multi-team environments [9], [41], [42]. As a result, hybrid project management approaches have emerged to balance these competing demands by combining iterative Agile practices with structured governance mechanisms.

Recent literature has explored hybrid project management from both conceptual and empirical perspectives. Ahmad et al. describe hybrid project management as the integration of Agile iterative practices with traditional governance structures, enabling organizations to maintain flexibility while ensuring managerial oversight [41]. Similarly, Bidgood and Meles observe that many organizations adopt hybrid practices informally, which can lead to inconsistencies in project outcomes due to the absence of standardized frameworks [8]. Research by Gren et al. further highlights the difficulty of selecting appropriate development methodologies in complex environments with uncertain or evolving requirements, reinforcing the need for adaptable hybrid frameworks [9].

Empirical studies also demonstrate limitations of purely Agile approaches in large-scale systems. Isetta and Sampietro show that Agile methodologies alone often fail to meet governance and compliance requirements in complex organizational contexts [42]. Complementing these findings, systematic reviews by Papadakis et al. and Reiff and Schlegel identify a growing interest in hybrid project management while noting the lack of standardized frameworks and limited empirical validation across different industries [43], [44]. More recent studies by Salas et al. and Székely et al. further emphasize the need for scalable and repeatable hybrid project management models capable of integrating governance, risk management, and stakeholder coordination across geographically distributed teams [45], [46].

While much of the hybrid project management literature originates from enterprise software and ERP implementations, the underlying principles—balancing flexibility with governance, coordinating distributed teams, and managing risk—are directly applicable to complex AI-driven systems. Empirical evidence from ERP projects demonstrates that structured hybrid approaches can improve project alignment, reduce failure rates, and enhance stakeholder satisfaction [8], [9], [41]. These findings suggest that hybrid project management principles can be effectively adapted for AI-driven healthcare systems in Bangladesh, where technical complexity and governance requirements must be balanced with the need for adaptability.

While hybrid project management frameworks address governance, coordination, and risk at the organizational and process levels, their effectiveness ultimately depends on how well these principles are translated into technical system design. In AI-driven healthcare systems, architectural decisions determine how managerial objectives such as scalability, reliability, ethical safeguards, and operational efficiency are implemented at the system level. This relationship is particularly significant in low-resource environments, where infrastructural limitations magnify the consequences of architectural trade-offs.

Accordingly, software architecture acts as a bridge between governance objectives and system-level execution, determining whether AI-based healthcare solutions can be sustainably deployed, maintained, and scaled in practice. The following section therefore examines the role of software architecture in supporting AI systems within low-resource environments.

2.4 Software Architecture for AI Systems in Resource-Constrained Environments

As software systems increasingly drive global economies, the relationship between software architecture and production economics has received growing attention. Architectural decisions such as modularity, scalability, and maintainability influence development costs, delivery timelines, and long-term value creation. These decisions affect both technical outcomes and financial performance. Understanding how architecture impacts production economics involves balancing technical choices with business outcomes to support sustainable return on investment (ROI) [6].

Research on software architecture broadly falls into four overlapping streams: (1) architecture quality and economic impact, (2) AI-assisted architectural decision making, (3) AI adoption in small and medium-sized enterprises (SMEs), and (4) strategic alignment of business and technology. Despite progress, explicit and computable integration between architectural decisions and economic outcomes remains limited [47].

2.4.1 Software Architecture Quality and Economic Impact

Prior studies establish that architectural quality attributes, including maintainability, modularity, and scalability, influence system longevity and operational costs. However, these effects are often treated indirectly rather than as explicit decision variables. Architectural decisions are typically assessed via technical metrics, while economic indicators, such as ROI or total cost of ownership (TCO), are addressed separately at the project management level [48].

Sepasi's Strategic Alignment Framework (SAF) connects organizational objectives to financial metrics using Objectives and Key Results (OKRs) and critical success factors. While SAF is effective at the strategic level, it does not operate at the software architecture layer and overlooks lifecycle cost implications stemming from technical design choices [68]. Similarly, Sudhabathula et al. present AI-driven enterprise architectures with automation insights but without ROI or production economics modeling [49].

2.4.2 AI-Assisted Architectural Decision Making

AI increasingly supports architectural tasks such as automated refactoring, pattern recommendation, and decision analysis. Bucaioni et al. survey AI techniques for architecture and highlight productivity benefits, though economic outcomes remain unquantified [47]. Some AI systems report success in scalable architectures and benchmarking (e.g., SWE Bench), but limitations in dataset scope and cost remain [50].

Generative AI has been applied to architectural documentation and refactoring, improving productivity rather than financial evaluation [51]. Eisenreich et al. explore AI-based translation from requirements to architecture, but without cost-effectiveness or ROI validation [48]. Archify, a recommender system for SMEs, supports architectural decisions without economic modeling or lifecycle cost analysis [52].

Other AI-driven innovations include AutoMaAS, a multi-agent architecture optimizing performance-cost configurations [53], and formal rule learning approaches that allow large language models to encode architectural constraints and reduce manual governance [54].Saga pattern-based microservice reference architectures facilitate resilience and scalability decisions in distributed systems, though economic evaluation remains unaddressed [55].

2.4.3 AI Adoption and SME Constraints

SMEs face constraints in budget, skills, and infrastructure when adopting AI for architecture [56].Hussain and Rizwan propose a prescriptive framework emphasizing readiness and strategic alignment, but it omits economic evaluation of architectural decisions [56]. Oldemeyer et al. and related studies highlight cost pressures leading SMEs to prioritize short-term delivery over long-term architectural sustainability [6], [50], [57]. Ozbayburtlu et al. present typologies of SaaS companies and their investment dynamics to guide AI product roadmap prioritization [58].

Overall, the reviewed literature demonstrates that software architecture plays a decisive role in enabling scalable, maintainable, and economically viable AI systems, particularly in low-resource environments. Architectural choices related to modularity, cloud integration, and resource optimization directly influence system sustainability, operational cost, and long-term value creation. However, existing studies largely focus on technical performance, with limited empirical linkage between architectural decisions and downstream quality outcomes such as reliability, robustness, and operational risk—especially in AI-driven healthcare systems deployed under economic and infrastructural constraints

2.5 Quality Assurance and Testing of AI-Based Software

Software quality assurance plays a critical role in ensuring the reliability, correctness, and maintainability of modern software systems, particularly as development practices increasingly incorporate automation and artificial intelligence. As systems grow in complexity, traditional testing approaches are being augmented and, in some cases, transformed by AI-driven techniques that aim to improve efficiency, accuracy, and adaptability across the software development lifecycle.

2.5.1 Role of Software Testing in Development

Software testing is integral to the development lifecycle, offering stakeholders insights into system quality and identifying unexpected behaviors or faults. Testing can be manual—executed without automation—or automated, utilizing scripts and tools to perform predefined test cases [59].

Testing methods are generally categorized as **black-box, white-box, or gray-box**, each ensuring software correctness from different perspectives. Key testing stages include design, development, release, and post-release maintenance, with

system testing evaluating how software components interact holistically. Regression testing remains critical across all stages, particularly when introducing new code or features, ensuring that updates do not disrupt existing functionality [60].

2.5.2 Evolution of Testing Approaches

Over the past two decades, testing has evolved from manual processes to automated frameworks such as Selenium, and now AI-based testing with autonomous "test bots" [61]. Integrating artificial intelligence and machine learning enhances testing by enabling systems to learn from data patterns and make decisions autonomously, reducing reliance on manual intervention and increasing efficiency [62].

2.5.3 Specialized AI Testing Techniques

Several advanced AI testing techniques have been developed to further improve quality assurance:

- **Differential Testing:** Identifies discrepancies across software versions or configurations [63].
- **Visual AI Testing:** Evaluates visual aspects of applications to ensure alignment with design specifications [64].
- **Declarative Testing:** Simplifies test creation, execution, and management through an intuitive and flexible paradigm [65].
- **Self-Healing Automation:** Automatically detects and resolves test errors, maintaining test accuracy without manual intervention [59].

Formica et al. proposes integrating AI techniques into automated test case generation, employing evolutionary algorithms, grammar-based fuzzing, machine learning, inter-procedural control dependency analysis, and behavioral modeling to improve efficiency [66]. Kumar et al. utilize reinforcement learning to prioritize test cases for fault detection, demonstrating improved regression testing outcomes across five case studies [67].

Yang et al. introduced a directed search method with an improved whale optimization algorithm for test case prioritization, achieving notable results in fault detection, statement coverage, and branch coverage [68]. Lyu et al. examined issue-based traceability, highlighting its benefits and challenges and suggesting strategies to enhance its effectiveness in software processes [69].

Khaliq et al. emphasize AI's potential to accelerate testing processes and improve accuracy, while acknowledging challenges such as data insufficiency and handling large workloads [70]. Arrieta et al. proposes Dynamic Adaptive Seeding (DAS) for search-based test selection, optimizing coverage, efficiency, and fault detection [71]. Pan et al. highlighted the importance of Test Case Selection and Prioritization (TSP) using machine learning to provide early feedback and improve regression testing [72]. Formica et al. demonstrated search-based software testing driven by automatically generated and manually defined fitness functions,

emphasizing the quality of fitness functions derived from domain knowledge and ML models [66].

Finally, Kumar and Kaur suggest a hybrid MCDM approach combining BWM and TOPSIS for selecting optimal testing methods based on cost, schedule, and resources [67]. Whang et al. discussed data preparation and quality assurance in AI-based software engineering, emphasizing tools like TFDV and ActiveClean to ensure fairness and reliability [73].

2.5.4 Overview of AI-Based Testing Tools

AI-driven testing tools have emerged as a key innovation in software quality assurance, providing enhanced efficiency, accuracy, and automation. Tools such as Functionize, Appvance, TestCraft, and Applitools demonstrate unique functionalities for diverse testing needs:

- Functionize leverages AI to enhance test creation and analysis, improving overall test efficiency.
- Appvance focuses on optimizing application quality, security, and performance through advanced AI algorithms.
- TestCraft offers a drag-and-drop interface, enabling testers to create automated tests without extensive coding knowledge.
- Applitools is widely used in automation, DevOps, and visual testing, detecting issues by inspecting app screens in a manner akin to human perception.

These AI-driven methods help organizations streamline testing workflows, reduce human error, and enhance product quality [69][70] [62], [74].

Overall, the literature indicates that AI-driven testing tools significantly enhance software quality assurance by improving test coverage, reducing manual effort, and enabling adaptive validation of complex system behaviors. However, the effectiveness of these tools is closely tied to the deployment environment in which AI systems operate. Factors such as scalability, computational availability, data accessibility, and operational resilience directly influence how testing frameworks are executed and maintained, particularly for data-intensive healthcare applications.

2.6 Cloud Computing Deployment for Scalable AI Healthcare Systems

Cloud computing has emerged as a foundational paradigm for deploying scalable, resilient, and data-intensive applications, making it particularly relevant for AI-driven healthcare systems. Mell and Grance formally defined cloud computing as an on-demand model providing configurable computing resources with minimal management effort, establishing the conceptual basis for elasticity, scalability, and service abstraction. These principles underpin modern cloud-native healthcare applications, enabling real-time processing of large volumes of patient data and AI-driven analytics [75].

Armbrust et al. highlighted the architectural and economic advantages of cloud computing, including elasticity, fault tolerance, and resource pooling. Such capabilities allow AI healthcare systems to dynamically scale in response to fluctuating workloads, a critical requirement for automated mental health screening tools that process data from multiple users simultaneously [76]. Buyya et al. further emphasized virtualization, dynamic provisioning, and service-oriented architectures as key enablers for deploying compute-intensive and data-driven applications on the cloud, reinforcing the suitability of cloud platforms for AI applications in healthcare [77].

Auto-scaling and elasticity mechanisms have been extensively studied as essential features of cloud systems. Lorido-Botrán et al. surveyed auto-scaling techniques, showing that dynamic resource allocation improves system responsiveness and cost efficiency. These mechanisms directly support the deployment of AI healthcare platforms, ensuring availability and performance even under peak demand [78].

Security, privacy, and network isolation are critical in healthcare applications due to sensitive patient data. Subashini and Kavitha analyzed security concerns in cloud service models, emphasizing the importance of access control, network segmentation, and secure communication channels. Implementing Virtual Private Cloud (VPC) architectures, strict access policies, and encryption aligns with regulatory requirements and ensures patient data confidentiality [79].

System migration and cloud adoption strategies have also been explored in prior research. Subashini examined end-to-end application migration to cloud platforms, demonstrating improvements in scalability, reliability, and operational efficiency, while Kahn et al. highlighted governance and fault tolerance considerations in large-scale healthcare data systems. These findings underscore the importance of structured cloud adoption strategies for AI healthcare solutions [79], [80].

Cloud availability and fault tolerance are vital to maintaining uninterrupted healthcare services. Endo proposed collaborative cloud availability models to mitigate service outages, emphasizing resilience and continuous service delivery. For AI-driven mental health platforms, such mechanisms ensure that users can access screening, monitoring, and therapeutic interventions without disruption [81].

Finally, vendor-specific frameworks provide practical guidance for cloud-based system design. The Amazon Web Services (AWS) Well-Architected Framework outlines principles for security, reliability, performance efficiency, and cost optimization. These guidelines inform architectural decisions in AI healthcare deployments, including the use of load balancing, auto-scaling groups, and secure networking to support high availability and operational efficiency [82].

Collectively, these studies demonstrate that cloud computing offers the scalability, resilience, and security required for AI-driven mental health systems, enabling efficient data processing, reliable service delivery, and secure handling of sensitive patient information. However, while cloud platforms address technical scalability, their integration with AI models, compliance with healthcare regulations, and cost optimization strategies lack sufficient empirical validation, particularly in low-resource and culturally diverse contexts.

2.7 Synthesis and Research Gaps

The literature on AI-driven mental health systems, human-centered AI, agile governance, software architecture, AI-based testing, and cloud computing highlights significant technological progress and potential for improving accessibility, efficiency, and scalability in low-resource contexts. Across these domains, AI has been applied to predictive diagnostics, automated decision support, conversational agents, software optimization, and scalable deployment. However, critical gaps persist that constrain the operational, ethical, and economic impact of these systems.

A central theme emerging from the literature is the **limited consideration of real-world integration and operational sustainability**. In mental health applications, studies predominantly focus on predictive accuracy, while overlooking long-term adoption, user engagement, cultural adaptation, and deployment feasibility, particularly in low-resource contexts such as Bangladesh. Similarly, human-centered AI research identifies the lack of frameworks that embed ethical, cultural, and operational considerations into requirements engineering, resulting in AI systems that may be technically effective but fail to align with user needs or contextual constraints.

In software engineering and development practices, the literature reveals gaps in **systematic governance, hybrid project management, and economic evaluation**. Existing Agile and distributed team studies emphasize coordination, psychological safety, and framework-specific practices but rarely provide integrated models that balance autonomy, standardization, and alignment across large-scale distributed environments. Similarly, research on hybrid project management shows that combining Agile flexibility with traditional governance can improve stakeholder engagement, iterative delivery, and compliance in complex systems, yet current frameworks often lack scalability, empirical validation, and systematic integration of technical, operational, and human dependencies. Likewise, AI-assisted software architecture demonstrates gains in performance and automation but fails to quantify economic outcomes such as ROI, TCO, or long-term operational value, particularly in SMEs and low-resource contexts. Collectively, these gaps highlight the need for a **scalable, adaptable, and empirically validated framework** that integrates human-centered governance, hybrid project management, and economic considerations to support the lifecycle of complex, AI-driven, culturally adaptive systems.

Within **AI-based software testing**, while advanced tools enhance automation, efficiency, and fault detection, there is limited research on cost-benefit analysis, lifecycle integration, and adaptive testing strategies responsive to evolving requirements or production data. Moreover, evaluation metrics remain predominantly technical, underrepresenting usability, maintainability, and operational impacts.

Finally, in **Cloud Computing** for AI healthcare systems, despite the clear advantages of scalability, elasticity, and resilience, empirical studies on cost-effectiveness, real-time integration, security implementation, and hybrid cloud strategies remain scarce, particularly for low-resource healthcare environments.

Collectively, these gaps reveal a **broader, cross-cutting research opportunity:** there is a need for frameworks and methodologies that integrate **technical optimization, human-centered design, economic evaluation, governance,**

and scalable deployment into a unified approach. Addressing these gaps would enable AI-driven mental health systems to be not only accurate and efficient but also operationally viable, ethically sound, culturally appropriate, and economically sustainable in low-resource and SME contexts.

Table 2.1: Summary of Key Advancements and Research Gaps Across Relevant Sub-Domains

Sub-Domain	**Key Advancements**	**Research Gaps / Limitations**
AI in Mental Health Systems	Predictive diagnostics, automated screening, personalized support, conversational agents, LLM integration for journaling and therapy	Focus on predictive accuracy; limited real-world deployment, adoption, and scalability; underexplored user engagement and long-term use; inadequate cultural and linguistic adaptation; scarce empirical validation; ethical, privacy, and trust issues in low-resource populations
Human-Centered AI and Requirements Engineering	Ethical, cultural, and user-centered design principles; bias and transparency awareness	Lack of systematic frameworks integrating human-centered AI into formal requirements engineering; limited operationalization in real-world AI systems
Agile Governance and Project Management in Distributed Teams	Psychological safety, communication and coordination, tailored Agile methods, hybrid Agile–traditional approaches	Absence of scalable governance frameworks balancing autonomy, alignment, flexibility, and accountability across distributed teams; limited empirical validation for large-scale systems
Software Architecture for AI Systems in Low-Resource Contexts	Automation, decision support, performance optimization, improved scalability and modularity	No clear linkage between architectural decisions and economic outcomes (ROI, TCO); SME and low-resource constraints often ignored
Quality Assurance and Testing of AI-Based Software	AI-assisted test automation, self-healing automation, differential testing, ML-based test prioritization	Limited cost–benefit evaluation; weak CI/CD integration; unrealistic assumptions about data quality and expertise; usability and operational impact often overlooked
Cloud Computing for Scalable AI Healthcare Systems	Cloud scalability, elasticity, autoscaling, fault tolerance, secure architectures	Limited cost-benefit analysis in low-resource contexts; lack of empirical studies on security, privacy, and hybrid-cloud strategies; insufficient cultural adaptation

Building on these identified gaps, this research proposes a unified framework

that integrates AI-driven mental health screening, human-centered requirements engineering, governance-aware development practices, software architectural alignment, quality assurance strategies, and scalable cloud deployment. The aim is to address the limitations of existing approaches by providing a structured, contextually appropriate, and economically sustainable solution for low-resource environments.

The following chapter presents the research methodology adopted in this study. It outlines the Design Science Research (DSR) approach used to systematically design, develop, and evaluate the proposed artifact, as well as the data sources, ethical considerations, and research boundaries that guide the overall investigation.

3 Research Methodology

This chapter presents the research methodology adopted to design, develop, and evaluate the proposed artifact. The study follows the Design Science Research (DSR) paradigm, which is appropriate for solving real-world problems through the creation and systematic evaluation of innovative artifacts.

The chapter is structured as follows. Section 3.1 introduces the research paradigm. Section 3.2 describes the Design Science Research process and explains how each phase is applied in this study. Section 3.3 discusses the data sources used to support the research. Section 3.4 outlines the ethical considerations embedded within the system design. Finally, Section 3.5 defines the scope and boundaries of the research.

3.1 Research Paradigm

This research adopts the **Design Science Research (DSR)** paradigm. Design Science Research is appropriate when the primary objective is to design, develop, and systematically evaluate an innovative artifact intended to solve a real-world problem.

Unlike purely empirical research that focuses on hypothesis testing or statistical generalization, DSR emphasizes the creation of purposeful artifacts and the rigorous assessment of their utility, relevance, and feasibility.

The primary artifact developed in this study is the **SAEAF** for AI-assisted mental health screening in Bangladesh. The research focuses on architectural design, governance integration, and economic sustainability rather than clinical diagnosis or AI model accuracy benchmarking.

Having outlined the Design Science Research process used to guide the development and evaluation of the artifact, the following sections describe the supporting data sources, ethical considerations, and research boundaries that inform and constrain the study.

3.2 Design Science Research Process

This study follows the established six-phase Design Science Research (DSR) process proposed by Peffers et al. [83] and grounded in the Design Science framework described by Hevner et al. [84]. The DSR methodology provides a structured approach for developing and evaluating artifacts intended to solve identified real-world problems through iterative design, development, and evaluation cycles.

The six phases of the DSR process applied in this study are described below.

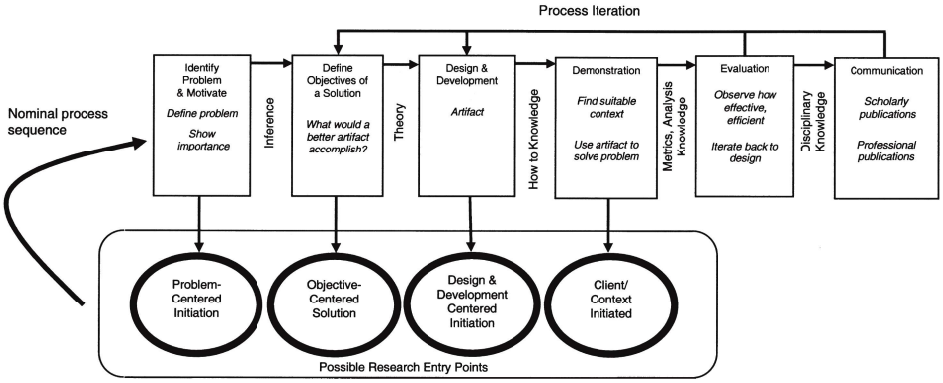


Figure 1: Design Science Research Process (Adapted from Peffers et al.)

3.2.1 Problem Identification and Motivation

The problem addressed in this research was identified through a comprehensive review of existing literature on mental health prevalence in Bangladesh, with particular attention to studies highlighting the widespread presence of depression, anxiety, and stress across different population groups. Additional insights were obtained from the analysis of validated Bangla implementations of the DASS-21 assessment instrument, which demonstrate the feasibility of culturally adapted psychological screening tools. The review further examined structural barriers that limit access to mental health services, including social stigma, lack of trained professionals, and geographical concentration of services in urban areas. In addition, challenges associated with the sustainability and deployment of digital systems in low-resource environments were analyzed. Together, these findings established the need for a culturally adaptive and economically sustainable digital screening architecture.

These findings are grounded in the literature discussed in Chapter 2, particularly Sections 2.1 and 2.2, which highlight the limitations of existing AI-based mental health systems and the need for culturally adaptive and human-centered approaches.

3.2.2 Define Objectives of the Solution

Based on the identified research gaps, the proposed solution is designed to meet several key objectives. The system must support bilingual interaction in both Bangla and English to ensure accessibility across diverse user groups. It must provide culturally sensitive screening interactions that respect local linguistic expressions and social contexts. The system is designed as a screening tool rather than a diagnostic platform, offering structured referral pathways to encourage professional consultation where necessary. From a technical perspective, the solution must support scalable deployment through cloud infrastructure while maintaining privacy-by-design principles to protect sensitive user data. Furthermore, governance mechanisms must be integrated within the development process to ensure ethical compliance, transparency, and responsible use of AI-driven technologies.

These objectives are derived directly from the research questions defined in Section 1.X, ensuring alignment between the problem definition and the proposed

solution.

3.2.3 Design and Development of the Artifact

The artifact developed in this research consists of a conceptual and architectural framework that integrates several complementary components. At its core is the SAEAF, which structures the system into layered architectural components aligned with economic sustainability considerations. The artifact also incorporates an AI-assisted adaptive interaction module designed to enhance user engagement and personalize screening interactions. In addition, Agile governance mechanisms are embedded within the development workflow to support iterative system evolution while maintaining oversight and compliance. A hybrid project management structure is proposed to balance flexibility and governance during system development. Finally, the architecture includes a cloud-based Infrastructure-as-a-Service (IaaS) deployment strategy designed to operate efficiently within the economic and infrastructural constraints of low-resource environments. It should be noted that the artifact is developed at the architectural and conceptual level rather than as a full-scale production deployment.

3.2.4 Demonstration

The proposed artifact is demonstrated through multiple conceptual and analytical representations that illustrate its structure and operational logic. These demonstrations include architectural diagrams describing the layered system design, workflow simulations that illustrate how users interact with the screening process, and scenario-based usage models representing typical system interactions in real-world contexts. Additionally, layer interaction mapping is used to show how different components of the architecture communicate and coordinate during system operation. These demonstration methods help illustrate the logical coherence of the proposed framework and its feasibility for practical implementation.

3.2.5 Evaluation

The evaluation of the proposed artifact is conducted through several analytical approaches designed to assess its conceptual validity and feasibility. First, problem–solution alignment analysis is used to determine whether the proposed architecture effectively addresses the challenges identified in the problem definition stage. Scenario-based architectural validation is then applied to assess how the system performs under representative usage situations. Economic sustainability considerations are evaluated through architectural reasoning within the SAEAF framework, examining how design decisions influence resource efficiency and operational feasibility. Governance suitability is also assessed to determine whether the proposed development approach supports ethical oversight and responsible AI deployment. Finally, ethical boundary analysis is conducted to ensure that the system maintains clear limitations as a screening tool rather than a clinical diagnostic platform. It is important to note that the scope of this research does not include empirical clinical trials or quantitative benchmarking of AI model performance.

3.2.6 Communication

The results of this research are communicated through multiple academic channels. The primary communication medium is this thesis document, which presents the research problem, methodology, artifact design, and evaluation results in a structured and comprehensive format. In addition, selected aspects of the research have been prepared for dissemination through academic publication, enabling the proposed architectural and governance framework to contribute to ongoing scholarly discussions on AI-driven mental health systems and software engineering practices for low-resource environments.

3.3 Data Sources

The study draws upon a structured combination of peer-reviewed research, validated empirical findings, and established software engineering theory. Importantly, the proposed framework is not developed solely from secondary literature; it integrates previously published and empirically validated research contributions by the author alongside established academic foundations.

The primary data and knowledge sources include:

- **Author's Peer-Reviewed Publications:** Previously published conference papers contributing validated sub-frameworks and empirical findings in:
  - Agile Governance for distributed software teams
  - Hybrid Project Management for large-scale ERP implementations (empirically validated)
  - Software Architecture and production economics
  - Cloud migration and secure infrastructure deployment

  These works provide foundational components that are synthesized into the unified Software Engineering Framework proposed in this thesis.

- **Preprint Research on AI-Based Testing:** A preprint study examining AI-assisted software testing practices in Bangladeshi software companies contributes insights into adaptive testing strategies integrated within the framework.

- **Validated Bangla DASS-21 Findings:** Empirical mental health screening data using the validated Bangla version of DASS-21 provides contextual grounding for the case study application.

- **Peer-Reviewed Literature:** Established academic literature on mental health systems, human-centered AI, culturally adaptive systems, software architecture, agile governance, and cloud economics supports theoretical alignment and comparative grounding.

- **Software Engineering Theory and Standards:** Established principles from requirements engineering, architectural design theory, governance models, and cloud infrastructure economics inform the structural design of the proposed framework.

No primary clinical experimentation or large-scale national deployment data is included within the scope of this research. The focus remains on software engineering framework design, structural integration, and analytical evaluation within a validated case study context.

3.4 Ethical Considerations

Ethical responsibility is a central concern in the design and conceptual development of AI-driven mental health systems. In this study, ethical considerations are not treated as external constraints but are explicitly incorporated into the system architecture and development process.

Specifically, the system integrates ethical safeguards through multiple mechanisms. First, it enforces a strict separation between screening functionality and clinical diagnosis, ensuring that the system does not provide medical decisions but instead encourages professional consultation. Second, privacy-by-design principles are embedded within the architecture, including secure data storage, controlled access mechanisms, and minimal data retention policies. Third, informed consent is incorporated into the user interaction flow, requiring users to acknowledge the purpose, limitations, and data usage policies before engaging with the system. Finally, governance mechanisms such as auditability, explainability checkpoints, and bias awareness are integrated into the development lifecycle to ensure responsible AI behavior.

In addition, the system incorporates privacy-by-design principles throughout the architectural design. Sensitive user data related to psychological assessments must be handled with strict confidentiality, ensuring that personal information is protected during data collection, storage, and processing. The system architecture therefore emphasizes secure data handling mechanisms, responsible AI interaction, and transparency in how user information is processed.

Consent management is another critical component of the ethical framework. Users must be informed about the purpose of the screening process, the non-diagnostic nature of the system, and the ways in which their data may be used. By embedding these safeguards into the architectural design and governance processes, the system aims to support responsible AI deployment while maintaining user trust and ethical compliance.

3.5 Research Scope and Boundaries

Clearly defining the scope of the research is necessary to ensure methodological clarity and to avoid overstating the contributions of the study. This research focuses primarily on the architectural and governance aspects of developing AI-assisted mental health screening systems for low-resource environments.

Within the scope of this research are the architectural design of the proposed system and its alignment with economic sustainability considerations. The study also examines the integration of governance mechanisms within the development process, including the use of Agile governance principles and hybrid project management structures. In addition, the research explores the conceptual integration of AI components within the screening architecture and evaluates the feasibility of deploying such systems within economically constrained environments.

At the same time, several aspects fall outside the scope of this thesis. The research does not include clinical validation trials or medical studies aimed at validating psychological outcomes. Similarly, detailed benchmarking of AI model accuracy is not conducted, as the focus of the work lies primarily in system architecture and governance rather than algorithmic optimization. Large-scale usability testing and quantitative cost simulation modeling are also excluded from the scope of this research.

These boundaries ensure that the research remains focused on architectural design, governance integration, and conceptual feasibility. They also establish a clear distinction between software engineering contributions and areas requiring future clinical or large-scale empirical validation.

3.6 Mapping of Research Objectives to Subsequent Chapters

To systematically address the research objectives defined in Chapter 1, this study follows a structured Design Science Research (DSR) process in which each subsequent chapter contributes to the design, development, governance, validation, and evaluation of the proposed research artifacts. Figure 2 illustrates how the research objectives are operationalized through a continuous design-to-evaluation pipeline across Chapters 4 to 9.

Chapter 4 focuses on requirements engineering and validation as a foundational activity within the DSR methodology. This stage was conducted to fulfill Objectives 1, 2, and 3 by identifying functional, cultural, bilingual, usability, and accessibility requirements necessary for developing a culturally adaptive AI-driven mental health screening system suitable for the Bangladeshi context. Requirement validation was additionally performed to ensure that the proposed system design aligns with stakeholder expectations and real-world contextual constraints before architectural and governance decisions were introduced.

Building upon the validated requirements, Chapter 5 develops the Unified Agile Governance Framework (UAGF) to fulfill Objective 4. This chapter establishes the governance and hybrid project management processes required to manage AI-driven and distributed software development environments. The governance model was developed as part of the DSR artifact construction process to provide structured coordination, accountability, ethical oversight, and iterative development support for complex healthcare-oriented systems.

Chapter 6 addresses Objective 5 through the development of the Software Architecture–Economics Alignment Framework (SAEAF). This stage was conducted to translate validated requirements and governance principles into a structured architectural framework capable of supporting scalability, sustainability, op-

erational feasibility, and economic alignment in low-resource environments. Architectural design and economic evaluation were therefore treated as core components of the proposed software engineering framework.

Chapter 7 extends the SAEAF framework by incorporating quality assurance and AI-based testing mechanisms. This stage was necessary to ensure that the proposed system satisfies reliability, maintainability, safety, and operational quality requirements associated with AI-driven healthcare systems. AI-assisted testing and validation processes were included as part of the framework to support continuous quality assurance and risk reduction throughout the system lifecycle.

Chapter 8 focuses on deployment and operational considerations to fulfill Objective 6. This stage evaluates cloud deployment models, scalability strategies, infrastructure feasibility, and operational sustainability for AI-enabled healthcare systems operating within low-resource environments. These deployment analyses were necessary to assess the practical feasibility of implementing the proposed frameworks beyond conceptual architectural design.

Finally, Chapter 9 consolidates and evaluates the outcomes of the proposed artifacts developed throughout the research process. This evaluation stage examines the effectiveness of UAGF and SAEAF from governance, architectural, operational, and usability perspectives, thereby assessing how successfully the proposed frameworks address the research objectives and overarching research problem.

As illustrated in Figure 2, the research progresses as an interconnected pipeline in which each chapter fulfills a specific role within the DSR methodology while collectively contributing to the development and evaluation of an integrated software engineering framework for designing, governing, and deploying AI-driven culturally adaptive mental health systems in Bangladesh.

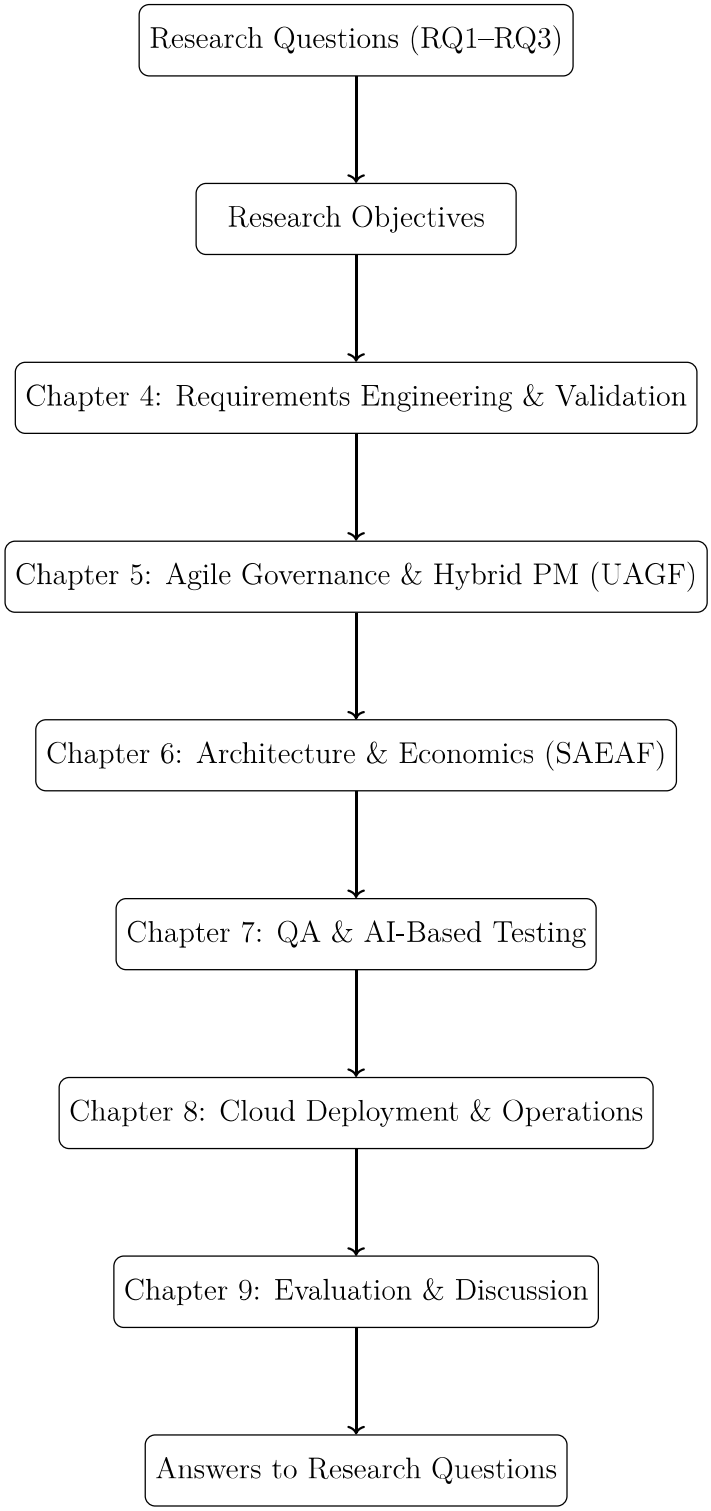


Figure 2: Flow of research contributions across Chapters 4–9

4 Requirements Engineering & Validation

4.1 Introduction

Requirements Engineering (RE) plays a critical role in the development of socio-technical systems, particularly in sensitive domains such as mental health [11]. In such contexts, RE extends beyond the identification of technical system functionalities and must also address issues related to linguistic inclusivity, cultural sensitivity, ethical safeguards, and trust-building mechanisms. These aspects are especially important when deploying digital mental health technologies in low-resource environments such as Bangladesh, where cultural perceptions and language preferences strongly influence user engagement and acceptance [14].

This chapter presents the requirements engineering and validation process followed in the design and development of the proposed bilingual and culturally adaptive mental health screening system based on the DASS-21 instrument. The requirements specification was developed through a structured process that incorporates stakeholder analysis, functional and non-functional requirements identification, and validation through expert review and user testing. The overall process aligns with the Human-Centered Design (HCD) methodology discussed in earlier chapters and supports the empirical and architectural findings reported in the accompanying research work [10]. By integrating user needs, ethical considerations, and cultural adaptation, the chapter establishes a comprehensive framework for designing accessible digital mental health screening tools suitable for the Bangladeshi context.

4.2 Stakeholder Analysis

A comprehensive stakeholder analysis was conducted to identify individuals and groups who interact with, influence, or are affected by the proposed mental health screening system. In digital mental health technologies, stakeholder identification is particularly important because system design decisions may directly affect psychological well-being, ethical responsibility, and healthcare accessibility.

For analytical clarity, stakeholders were categorized into three groups: primary, secondary, and tertiary stakeholders. This classification reflects the degree of interaction each group has with the system and their role in influencing system design and sustainability.

4.2.1 Primary Stakeholders

Primary stakeholders represent users who directly interact with the system interface and therefore exert the greatest influence on usability requirements and design decisions. The primary user group consists of individuals from the general population who use the platform for self-screening of mental health conditions. These users typically fall within the age range of 18 to 55 and may experience symptoms related to stress, anxiety, or depression. For many individuals, digital tools offer an accessible and stigma-free method for initial psychological self-assessment.

Within this group, particular attention is given to at-risk users whose screening scores fall within moderate to severe categories. For these individuals, the design of feedback messages, referral guidance, and emotional framing becomes critically important. The system therefore emphasizes requirements related to clarity of communication, emotional safety, anonymity, and linguistic comfort in order to minimize the risk of distress or misinterpretation.

4.2.2 Secondary Stakeholders

Secondary stakeholders include professionals and institutions that do not directly interact with the system interface but benefit from its outputs and potential societal impact. Mental health professionals such as psychologists, psychiatrists, and counselors fall into this category. Early screening tools can assist these professionals by encouraging individuals to seek help earlier and by providing structured referral pathways that guide users toward appropriate mental health services.

Researchers and academic institutions also represent an important secondary stakeholder group. Aggregated and anonymized data generated by the system can provide valuable insights for population-level mental health analysis. Such data may help researchers identify trends in psychological well-being and contribute to the development of evidence-based interventions within the Bangladeshi context.

4.2.3 Tertiary Stakeholders

Tertiary stakeholders include actors who influence system sustainability, policy alignment, and long-term operational management. Policy makers and non-governmental organizations (NGOs) may utilize digital screening tools as scalable solutions for community-level mental health awareness and early detection initiatives. Their interest primarily lies in systems that are affordable, accessible, and adaptable to national healthcare strategies.

System maintainers and technical administrators also fall into this category. These stakeholders are responsible for ensuring system reliability, maintaining data security, implementing updates, and potentially integrating future analytical modules such as artificial intelligence-based risk prediction components.

4.3 Bilingual and Cultural Requirements

Linguistic and cultural inclusivity form a fundamental component of system accessibility in Bangladesh. Although English is commonly used in formal and academic settings, emotional expression and personal reflection are often more naturally

conveyed in Bengali. Therefore, the system was designed to accommodate both languages in order to improve comprehension, accessibility, and user comfort.

4.3.1 Bilingual Requirements

To address linguistic diversity among users, the system was designed to support both English and Bengali simultaneously. Each questionnaire item is displayed in both languages, allowing users to interpret questionnaire items using the language with which they are most familiar and emotionally comfortable. using the language they understand best. This dual-language presentation reduces the risk of misinterpretation and supports users with varying levels of English proficiency.

For example, DASS-21 questionnaire items such as:

"I found it difficult to relax"

were presented alongside the Bengali translation:

"আমার জন্য শান্ত হওয়া বা আরাম করা কঠিন ছিল"

Similarly, emotional terms such as "stress," "anxiety," and "depression" were carefully translated using contextually understandable Bengali expressions to avoid ambiguity or overly clinical interpretation.

The interface was also designed to support bilingual navigation and accessibility. Key interface elements such as:

- "Start Assessment" / "মূল্যায়ন শুরু করুন"
- "Submit" / "জমা দিন"
- "View Result" / "ফলাফল দেখুন"

were displayed bilingually to improve usability for users with mixed language familiarity.

In order to preserve semantic accuracy, the translation process followed a forward–backward translation methodology supported by bilingual domain experts. This approach ensured that the Bengali translations maintained conceptual equivalence with the original DASS-21 items. Presenting English and Bengali text side-by-side further improves comprehension and aligns with previously validated Bangla adaptations of the DASS-21 instrument [15].

4.3.2 Cultural Adaptation Requirements

Beyond language translation, cultural adaptation was necessary to ensure that the system reflects local norms related to emotional expression, mental health stigma, and help-seeking behavior. In many South Asian contexts, mental health conditions are often associated with social stigma, which may discourage individuals from seeking professional support.

To address this challenge, the system was designed to use non-clinical and non-judgmental language in feedback messages. Diagnostic terminology such as "You are clinically depressed" was intentionally avoided in order to prevent users from interpreting screening results as formal medical diagnoses. Instead, the system provides supportive and guidance-oriented feedback such as:

> "Your responses indicate that you may be experiencing emotional stress. Consider speaking with a mental health professional or trusted individual if these feelings persist."

This culturally sensitive wording was intended to reduce stigma, increase user comfort, and encourage willingness to seek professional support when necessary.

The system also avoids overly technical or culturally unfamiliar terminology that may be unfamiliar to general Bangladeshi users. For example, complex psychological terms were replaced with simpler and more conversational expressions commonly understood in local contexts.

Additionally, culturally relevant tone and contextual examples were incorporated to make the feedback more relatable for users in Bangladesh. The interface design prioritized simplicity, readable typography, and mobile-friendly interaction patterns because many users in low-resource environments primarily access digital services through smartphones with limited bandwidth.

Privacy-oriented interaction was also treated as a cultural requirement. Since mental health discussions are often considered sensitive in Bangladeshi society, the system minimizes unnecessary personal data collection and avoids displaying stigmatizing labels during user interaction.

Prior studies have shown that culturally mismatched digital tools can reduce user trust and engagement, particularly in South Asian populations [1]. By incorporating culturally sensitive language, bilingual interaction, privacy-conscious design, and supportive communication strategies, the system aims to increase accessibility, trust, and long-term user engagement.

4.4 Functional and Non-Functional Requirements

Functional and non-functional requirements were identified to ensure that the system fulfills both technical objectives and user-centered design goals. Functional requirements define the core capabilities of the system, whereas non-functional requirements describe quality attributes such as usability, reliability, and scalability.

4.4.1 Core Functional Requirements

The primary functional objective of the system is to provide an accessible platform for mental health self-screening using the validated DASS-21 instrument. The system first presents the DASS-21 questionnaire in a bilingual format, allowing users to view each question in both English and Bengali simultaneously. This presentation approach supports comprehension and reduces ambiguity.

Prior to beginning the screening process, the system collects a limited set of demographic information including age, gender, education level, occupation, income category, and place of residence. These variables support population-level analysis while maintaining user anonymity and avoiding the collection of personally identifiable information.

Once users complete the questionnaire, the system automatically calculates depression, anxiety, and stress scores according to the standardized DASS-21 scoring methodology. Based on these calculated scores, the platform classifies users into

severity categories ranging from Normal to Extremely Severe. Immediately after submission, the system generates personalized feedback messages that summarize the screening results in a clear and supportive manner.

For users whose scores indicate higher levels of psychological distress, the system additionally provides localized mental health resources and referral information. This feature is intended to encourage individuals to seek professional consultation and access available support services.

4.4.2 Non-Functional Requirements

Because the system handles sensitive psychological information, non-functional requirements were treated as equally important as functional capabilities. These requirements address system usability, performance, reliability, and long-term maintainability.

From a usability perspective, the system follows a mobile-first design approach to ensure compatibility with low-end smartphones commonly used in Bangladesh. The questionnaire is structured to be completed within approximately ten minutes in order to minimize cognitive load and prevent user fatigue. Clear instructions and appropriately spaced Likert-scale response options further support ease of use.

Performance and reliability requirements ensure that screening results are generated immediately after questionnaire submission and that scoring calculations remain consistent with established DASS-21 guidelines. Reliable performance is essential for maintaining user trust and preventing confusion.

In addition, the system was designed with scalability and maintainability in mind. The architecture allows deployment without specialized infrastructure, making it suitable for low-resource environments. At the same time, the system structure remains extensible so that future enhancements—such as artificial intelligence or machine learning-based analytical modules—can be integrated without significant redesign. These design considerations align with best practices for digital mental health interventions in low-resource settings.

4.5 Ethical Requirements

Ethical considerations were integrated directly into the requirements engineering process rather than being treated as post-design constraints. Because mental health information is highly sensitive, the system was designed to prioritize user safety, transparency, and responsible data handling.

Participation in the screening process requires explicit informed consent. Users are clearly informed about the purpose of the system, the non-diagnostic nature of the results, and the potential use of anonymized data for academic research. This approach promotes transparency and ensures that users retain control over their participation.

The system also clearly communicates that it does not provide clinical diagnosis. Instead, it functions as a preliminary screening tool intended to help individuals recognize potential indicators of psychological distress. When elevated risk levels are detected, users are encouraged to seek professional consultation rather than relying solely on automated feedback.

Privacy protection represents another key design principle. The system does not collect personally identifiable information, and all collected data are stored in anonymized form. This approach supports ethical data use while still enabling aggregated research analysis.

4.6 Pre-User Validation

Before large-scale system evaluation, multiple pre-user validation activities were conducted to ensure that the proposed bilingual mental health screening system satisfied the functional, linguistic, cultural, and usability requirements identified during requirements engineering. These validation activities formed part of the Design Science Research (DSR) evaluation cycle and were conducted to verify that the proposed artifact aligned with the research objectives related to accessibility, cultural adaptability, and human-centered AI design.

4.6.1 Expert Review

The bilingual questionnaire design, user interaction flow, and feedback mechanisms were reviewed by individuals with knowledge in mental health research, human-computer interaction (HCI), and software engineering. The review process focused on:

- linguistic consistency between English and Bangla questionnaire items,
- preservation of semantic meaning during translation,
- appropriateness of culturally sensitive terminology,
- usability of the questionnaire interface, and
- alignment with standard DASS-21 scoring procedures.

Particular attention was given to ensuring that the Bengali translations preserved the psychological intent of the original DASS-21 instrument while remaining understandable for local users. Feedback from the review process resulted in refinements to wording, interface presentation, and feedback tone to improve clarity and reduce ambiguity.

4.6.2 Pilot Survey and Initial User Validation

To evaluate the practical usability and linguistic accessibility of the proposed system, a pilot survey was conducted using a bilingual Google Forms-based implementation of the DASS-21 questionnaire. The survey collected responses from approximately 150 participants consisting primarily of students and young adults familiar with digital platforms.

The questionnaire contained all 21 DASS-21 assessment items presented in both English and Bangla simultaneously. Each item used a four-point Likert response scale ranging from “0 – Never” to “3 – Almost Always,” with bilingual response labels included to improve comprehension among users with varying levels of English proficiency.

Examples of bilingual questionnaire presentation included:

- “I felt scared without any good reason” alongside the Bangla translation "যথাযথ কারণ ছাড়াই আমি ভীত-সন্ত্রস্ত বোধ করতাম।"
- “I felt that life was meaningless” presented together with "জীবনটা অর্থহীন বলে মনে হত।"

The survey was distributed online through Google Forms, enabling remote participation and accessibility across different user groups. The purpose of this pilot survey was not clinical diagnosis but preliminary validation of:

- bilingual readability,
- cultural appropriateness,
- questionnaire clarity,
- response usability, and
- overall interaction experience.

Participant responses and distribution patterns obtained from this survey were later used during the empirical analysis phase presented in Chapter 9. Detailed statistical graphs and response distributions derived from the survey are therefore discussed in the evaluation chapter to avoid duplication.

4.7 Post-User Validation

Post-user validation was conducted to evaluate whether the implemented system successfully fulfilled the intended usability, accessibility, and operational objectives after real-world interaction with users.

4.7.1 Empirical Validation

Following the pilot validation phase, the system was evaluated using empirical response data collected through the deployed bilingual DASS-21 screening platform. In total, responses from more than 250 participants were analyzed during the evaluation process.

The collected data was used to examine:

- questionnaire completion behavior,
- usability and accessibility outcomes,
- consistency between DASS-21 subscales,
- bilingual interaction effectiveness, and
- overall user engagement patterns.

Preliminary analysis demonstrated high questionnaire completion rates, suggesting that the bilingual interface and simplified interaction flow were effective for users in low-resource and multilingual environments. Correlation analysis among depression, anxiety, and stress indicators also showed patterns consistent with findings reported in prior DASS-21 validation studies.

Detailed statistical analysis, response distributions, graphs, and evaluation results derived from participant data are presented in Chapter 9.

4.8 User Feedback Indicators

In addition to quantitative evaluation, qualitative observations collected during pilot testing and user interaction provided further insight into the effectiveness of the proposed system.

Many participants indicated that the bilingual presentation improved comprehension and made emotional self-reflection easier, particularly when sensitive psychological concepts were expressed in Bangla. Users frequently preferred reading emotional statements in Bengali while using English text as contextual reinforcement.

Participants also reported that the immediate feedback mechanism helped them better understand their emotional condition without feeling intimidated by clinical terminology. This supports the human-centered design objective of reducing psychological barriers associated with mental health screening.

Furthermore, several users expressed that the inclusion of supportive recommendations and referral guidance increased their willingness to consider seeking professional assistance when necessary. These observations suggest that the proposed system successfully aligns technical functionality with cultural sensitivity, accessibility, and user-centered design requirements.

4.9 Summary

This chapter presented a structured requirements engineering and validation framework for a bilingual and culturally adaptive mental health screening system. Through stakeholder analysis, functional and non-functional requirement identification, and rigorous validation procedures, the study established a comprehensive design foundation for the proposed platform.

By integrating ethical safeguards, linguistic accessibility, and culturally sensitive design principles within a human-centered development process, the system aims to improve accessibility and trust in digital mental health screening tools within Bangladesh. The validated requirements also provide a solid foundation for future enhancements, including the integration of advanced AI-based analytical capabilities discussed in subsequent chapters.

5 Agile Governance Process & Hybrid Project Management Model

The development of AI-driven software systems in distributed and low-resource environments introduces a dual managerial challenge: maintaining adaptability in the face of evolving requirements while ensuring sufficient governance, risk control, and ethical oversight. This tension is widely recognized in both Agile software engineering and project management literature, particularly for large-scale, multi-stakeholder, and socio-technical systems such as AI-based healthcare solutions. While Agile methodologies emphasize flexibility, rapid feedback, and user-centric delivery, they often lack formal governance mechanisms required for compliance, accountability, and risk mitigation in complex projects. Conversely, traditional project management approaches such as PMBOK and PRINCE2 provide strong governance and control but suffer from rigidity and delayed responsiveness. This trade-off has motivated growing interest in Agile governance and hybrid project management models that intentionally integrate agility with structured oversight. This chapter builds directly on the literature review gaps identified in Section 2.3 and leverages insights from two published studies—Unified Agile Governance Framework (UAGF) and the empirically validated Hybrid ERP Project Management Framework (HERP-PMF)—to formulate an Agile governance process and hybrid project management model tailored for AI-driven and distributed development contexts. The chapter synthesizes prior research on distributed Agile adaptation, team dynamics, governance alignment, and hybrid methodologies, and contextualizes them within the development of an AI-based mental health screening system in Bangladesh.

The UAGF forms the structural basis of the proposed governance model by defining the interaction between Agile execution and governance checkpoints. It ensures that decision-making, risk assessment, and ethical considerations are continuously integrated within the development lifecycle rather than treated as isolated phases.

5.1 Agile Governance in AI-Driven and Distributed Environments

Agile governance in the proposed model is defined as a structured yet flexible mechanism that embeds decision-making authority, accountability, and oversight within iterative development processes. In contrast to traditional governance models that operate as external control layers, the proposed approach integrates gov-

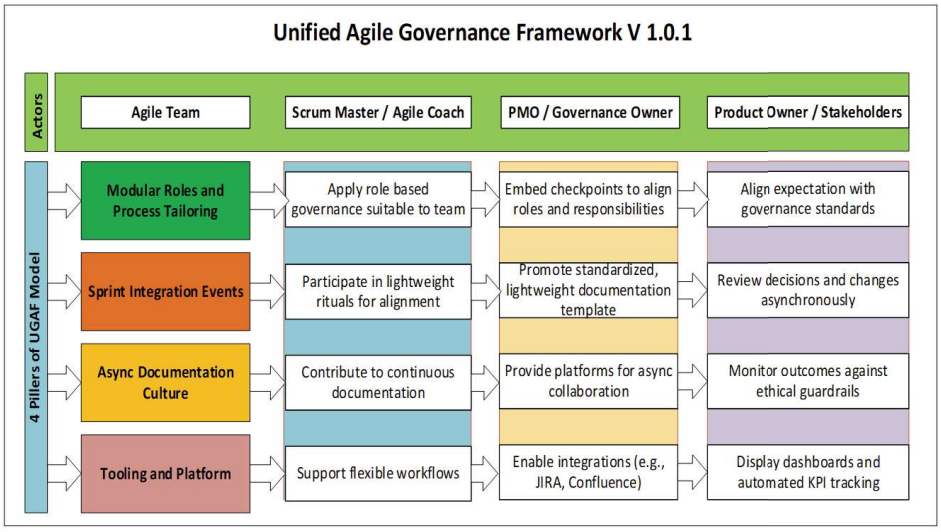


Figure 3: Unified Agile Governance Framework (UAGF)

ernance directly into Agile workflows.

In AI-driven systems, governance plays a critical role due to the presence of data dependency, ethical risks, and evolving system behavior. These challenges are further amplified in distributed environments where coordination, communication, and alignment cannot rely on co-located interaction.

To address these challenges, the proposed model incorporates:

- Clearly defined roles and decision hierarchies
- Embedded governance checkpoints within Agile iterations
- Structured communication protocols for distributed teams

Figure 3 illustrates how governance is positioned across the system lifecycle.

5.2 Team Dynamics, Psychological Safety, and Communication

As discussed in Section 2.3.2, prior literature highlights psychological safety, structured communication, and continuous feedback as critical success factors in distributed Agile environments [32], [33], [34], [35]. Building on these findings, the proposed governance model incorporates team-level mechanisms designed to strengthen collaboration, transparency, and adaptive learning within AI-driven and geographically distributed development teams.

Specifically, the model introduces:

- Structured retrospectives with optional anonymity
- Continuous documentation practices for transparency
- Feedback loops embedded within governance checkpoints

These mechanisms ensure that governance structures support collaboration, trust, and organizational learning rather than imposing rigid managerial control. In the context of AI-enabled mental health systems, such practices are particularly important because requirements, ethical considerations, and stakeholder expectations evolve continuously throughout the system lifecycle. The integration of psychological safety and transparent communication therefore supports both technical coordination and responsible governance within the proposed UAGF model.

5.3 Alignment of Agile Methods with Governance Structures

As reviewed in Section 2.3.3, existing studies demonstrate that no single Agile methodology is universally suitable for all project environments, particularly in large-scale, distributed, and AI-driven systems where governance, coordination, and compliance requirements vary significantly [32], [36], [37], [40]. In response to these limitations, the proposed governance model adopts a method-agnostic and adaptive approach in which Agile practices are selected and tailored according to project complexity, stakeholder requirements, and operational constraints.

Rather than enforcing a fixed methodology, governance mechanisms are designed to complement Agile execution by:

- Providing oversight without interrupting iteration cycles
- Supporting coordination across distributed teams
- Ensuring alignment with stakeholder, ethical, and compliance requirements

This adaptive governance structure enables the integration of Agile flexibility with strategic oversight, supporting the development of AI-enabled healthcare systems that require continuous iteration while maintaining accountability, traceability, and governance consistency. Within this research, these governance mechanisms form a core component of the proposed Unified Agile Governance Framework (UAGF), which operationalizes governance principles for distributed and AI-driven software engineering environments.

5.4 Hybrid Project Management for Complex Systems

To address the limitations of purely Agile and purely plan-driven approaches, the proposed model adopts a hybrid project management structure. This approach integrates iterative development practices with formal governance controls across the project lifecycle.

The hybrid model is particularly suitable for AI-driven systems due to:

- High uncertainty in requirements and system behavior
- Need for continuous risk and ethical evaluation

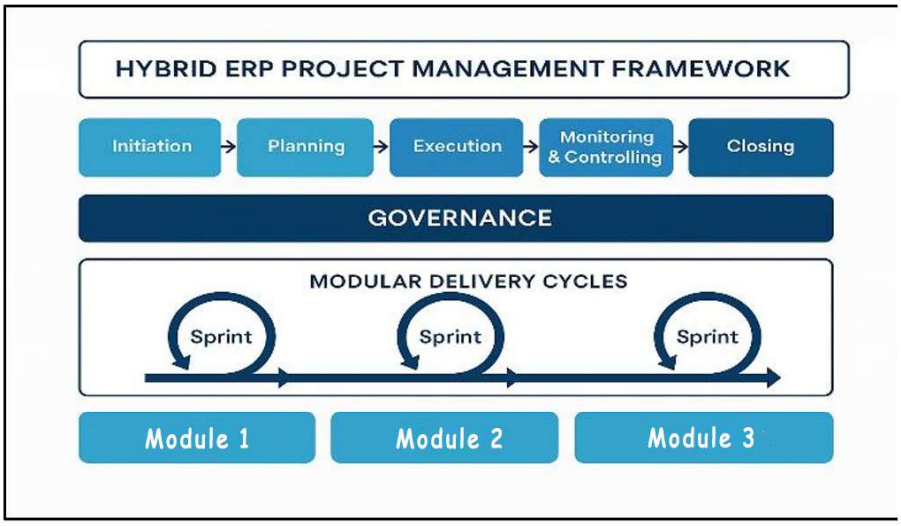


Figure 4: Conceptual Framework of Hybrid Project Management

- Multi-stakeholder coordination requirements

Figure 4 illustrates the conceptual structure of the hybrid model.

5.5 Proposed Agile Governance and Hybrid Project Management Model

Based on the identified gaps and design requirements, this research proposes an integrated Agile governance and hybrid project management model tailored for AI-driven mental health systems in low-resource environments.

5.5.1 Core Design Principles

The proposed model is grounded in three interrelated principles that guide the integration of governance, adaptability, and risk management within the development process.

- **Iterative Governance Checkpoints:** Governance is embedded throughout the project lifecycle via recurring checkpoints aligned with Agile sprint reviews. This approach enables continuous oversight, ethical review, and stakeholder alignment without undermining development adaptability. The overall process flow of the proposed UAGF model illustrating these checkpoints is presented in Figure 5.
- **Modular and Incremental Delivery:** System functionalities are decomposed into manageable modules that are delivered through Agile iterations. This modular approach reduces integration risks, supports early validation of system components, and aligns with the practical deployment constraints often present in low-resource environments. The modular and incremental delivery process adopted in the model is illustrated in Figure 6.

- **Adaptive Risk, Ethics, and Compliance Management:** Risk identification, ethical considerations, and compliance checks are revisited at each governance checkpoint. This ensures that technical, organizational, and societal perspectives remain aligned throughout the system development lifecycle.

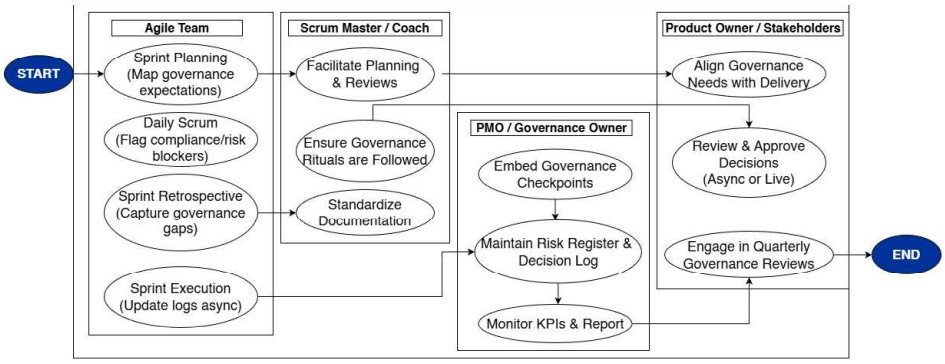


Figure 5: Process flow of the UAGF model

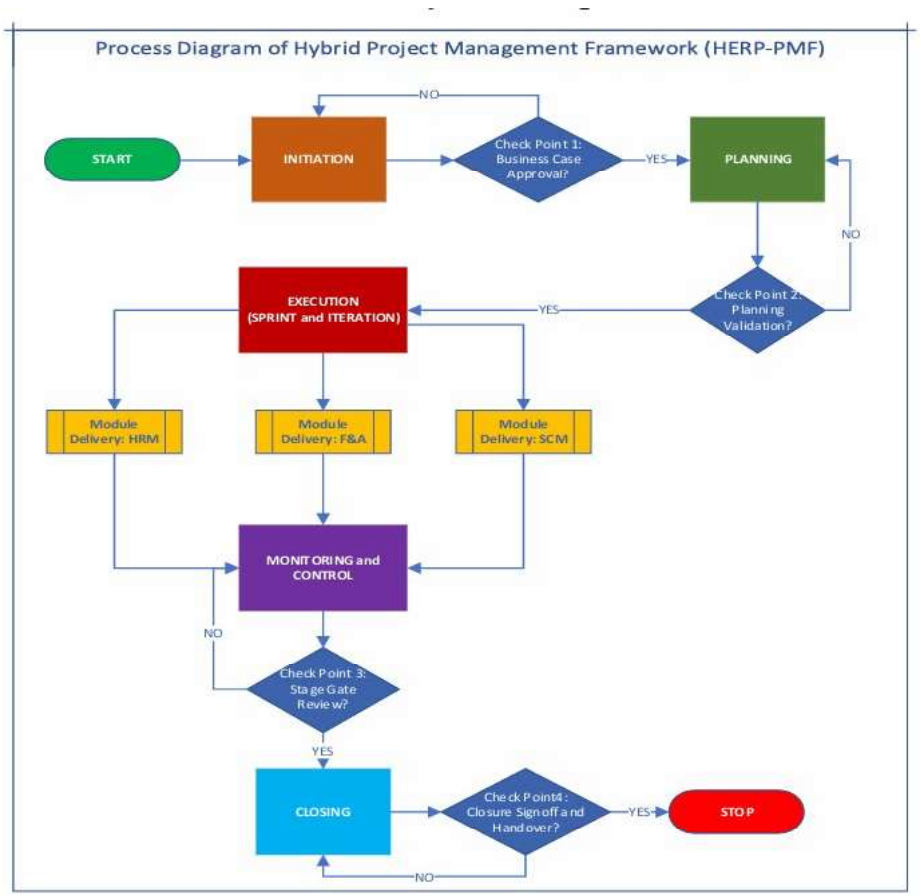


Figure 6: Modular and incremental delivery process

5.6 Governance Process Across the Project Lifecycle

The governance process spans the full project lifecycle while preserving Agile execution dynamics, Figure 4.

- **Initiation:** Feasibility Assessment, ethical feasibility assessment, and high-level stakeholder analysis.
- **Planning:** Architectural planning, risk register formulation, governance structure definition, and Agile backlog creation.
- **Execution:** Sprint-based development with continuous stakeholder feedback and embedded governance reviews.
- **Monitoring and Control:** Ongoing evaluation of scope, risk, ethics, and performance through governance checkpoints.
- **Closure:** Formal validation of outcomes, documentation of lessons learned, and transition to operational use.

This lifecycle-oriented governance ensures traceability, accountability, and adaptability across distributed teams.

5.7 Summary

This chapter presented a comprehensive Agile governance process and hybrid project management model for AI-driven and distributed software development. By synthesizing findings from Agile adaptation literature, psychological safety research, and empirically validated hybrid frameworks, the chapter addressed critical gaps related to governance, coordination, and risk management. The proposed model balances flexibility with control, providing a robust managerial foundation for developing ethical, scalable, and reliable AI-based healthcare systems in low-resource contexts.

While effective governance structures guide decision-making and delivery processes, their impact ultimately depends on how they are operationalized through concrete technical and architectural choices. Accordingly, the following chapter examines how these governance principles are translated into software architecture decisions, with particular attention to economic feasibility, scalability, and sustainability in resource-constrained environments.

6 Software Architecture & Economic Considerations

Software architecture constitutes the technical foundation through which governance principles, project management decisions, and system requirements are transformed into operational capabilities. In AI-driven healthcare systems deployed in low-resource environments, architectural choices have implications that extend beyond technical performance to encompass economic feasibility, sustainability, and long-term societal impact. Decisions related to modularity, deployment topology, scalability mechanisms, and resource allocation directly influence development cost, operational expenditure, and total cost of ownership (TCO), thereby shaping return on investment (ROI) and system viability.

Building on the Agile governance and hybrid project management model established in the previous chapter, this chapter presents a comprehensive examination of software architecture from both technical and economic perspectives. It synthesizes existing research on architecture quality attributes, AI-assisted architectural decision making, and constraints faced by SMEs and low-resource contexts, and advances this work by proposing and justifying a system architecture tailored for an AI-driven mental health screening platform. The chapter positions architecture as the execution layer of governance, where ethical, managerial, and economic objectives are concretely realized through design decisions.

6.1 Software Architecture and Economic Impact

Extant literature consistently demonstrates that architectural quality attributes—particularly modularity, scalability, maintainability, and fault tolerance—are closely associated with system longevity and lifecycle cost. Modular architectures reduce coupling between components, enabling incremental development and localized change, which lowers maintenance effort and enhances adaptability to evolving requirements. Scalability mechanisms influence infrastructure utilization and cost elasticity, while maintainability affects staffing requirements and long-term operational efficiency.

However, architectural and economic considerations are often analyzed separately. Architectural decisions are typically evaluated using technical metrics such as performance benchmarks, complexity measures, or reliability indicators, while economic measures such as ROI and TCO are addressed at higher levels of project management [48]. This separation limits decision-makers' ability to assess how specific design choices translate into financial outcomes.

Strategic alignment approaches, such as Sepasi's Strategic Alignment Frame-

work (SAF), attempt to connect organizational objectives with financial outcomes through Objectives and Key Results (OKRs) and critical success factors. However, such frameworks primarily operate at the strategic planning layer and provide limited guidance on how concrete architectural decisions—such as service decomposition, data storage strategies, or deployment models—affect lifecycle cost and sustainability. Similarly, AI-driven enterprise architecture proposals emphasize automation and decision support but often omit explicit modeling of production economics and cost trade-offs [49].

Table 6.1 presents key SME-oriented architectural features and their measurable economic impact, illustrating how specific design decisions translate into operational and financial outcomes.

These features collectively operationalize the linkage between architectural design decisions and measurable economic outcomes within the SAEAF framework.

6.2 Software Architecture–Economic Alignment Framework (SAEAF)

Within the overall software engineering framework proposed in this thesis, the **Software Architecture–Economic Alignment Framework (SAEAF)** constitutes a distinct and critical layer that operationalizes governance principles and human-centered requirements into deployable, economically sustainable system structures. This architectural–economic layer is responsible for translating abstract managerial, ethical, and contextual objectives into concrete design decisions that directly shape system scalability, reliability, cost efficiency, and long-term viability.

Drawing on the author's prior published work on software architecture and production economics [6], SAEAF formalizes the relationship between architectural quality attributes and economic outcomes. Unlike existing approaches that treat architecture and economics as loosely coupled concerns, the proposed framework explicitly positions architectural decisions as economic decision points. Modularity, deployment topology, data management strategies, and AI workload placement are treated not only as technical design variables, but also as mechanisms through which total cost of ownership (TCO), operational expenditure, and return on investment (ROI) are actively managed.

Figure7 presents SAEAF within the overall software engineering framework, illustrating its mediating role between Agile governance processes and downstream quality assurance and deployment activities. Governance inputs—such as ethical constraints, compliance requirements, and resource limitations—inform architectural decision boundaries, while architectural outputs establish the structural foundation upon which quality assurance and system validation are performed.

This layer is informed by three core architectural principles derived from the literature and adapted to low-resource AI healthcare contexts. First, modular decomposition is employed to isolate functional concerns and minimize change propagation, thereby reducing maintenance effort and long-term operational cost. Second, selective scalability is achieved through service-oriented design and controlled cloud integration, enabling computationally intensive AI components to scale independently while avoiding unnecessary infrastructure expenditure. Third,

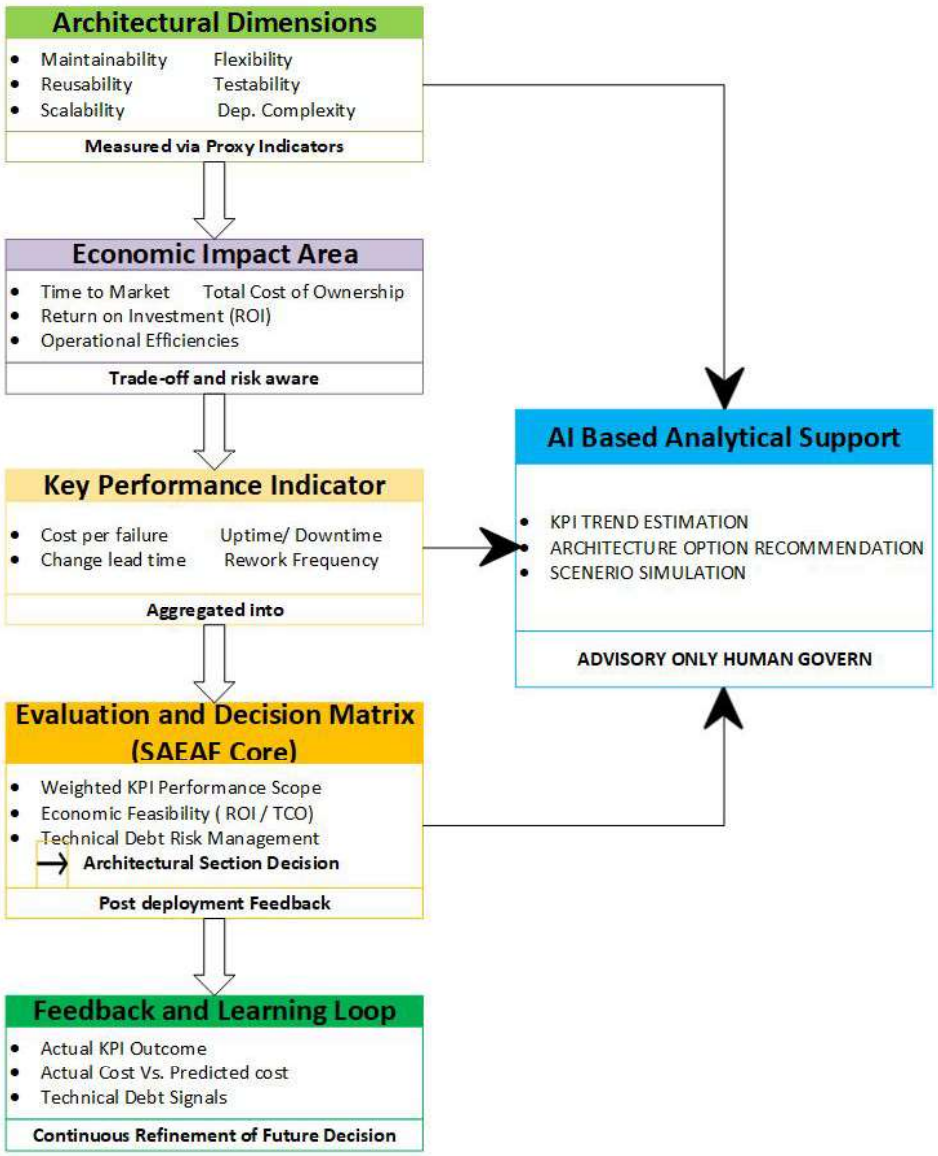


Figure 7: Proposed Framework: SAEAF

architectural simplicity and transparency are prioritized to lower operational risk, reduce dependency on specialized expertise, and support sustainable maintenance within constrained organizational settings.

By embedding economic reasoning directly into architectural design, the framework addresses a key research gap identified in prior studies, namely the absence of explicit and computable links between architectural decisions and economic outcomes in AI-driven systems [47], [48]. This is particularly relevant in low-resource healthcare environments, where architectural overengineering or uncontrolled scalability can undermine system sustainability and accessibility.

SAEAF thus serves as a unifying mechanism within the proposed software engineering framework, ensuring that system structure, cost efficiency, and governance objectives remain aligned throughout the system lifecycle. In the context of the mental health case study in Bangladesh, this layer enables the design of

an AI-driven, culturally adaptive system that is not only technically robust and ethically compliant, but also economically feasible and scalable within real-world constraints.

6.3 Proposed Software Architecture for the AI-Driven Mental Health System

In response to the identified gap, this research proposes a modular, service-oriented software architecture designed specifically for an AI-driven mental health screening system operating in low-resource contexts. The architecture is informed by the governance principles and hybrid project management model presented earlier, ensuring alignment with ethical requirements, scalability goals, and economic constraints. The proposed architecture is organized into loosely coupled functional layers: user interaction, application services, AI analytics, data management, and infrastructure services. The user interaction layer supports bilingual interfaces and culturally adaptive content delivery. Application services manage screening workflows, consent handling, and recommendation logic. The AI analytics layer encapsulates machine learning models for mental health screening, enabling independent evolution and controlled deployment. Data management services ensure secure storage, anonymization, and controlled access to sensitive health data. Infrastructure services provide deployment, monitoring, and resource management capabilities. This modular decomposition enables selective scaling and incremental enhancement, reducing upfront investment and allowing the system to evolve in response to user demand and regulatory requirements, table 6.2

6.3.1 Mathematical Model of SAEAF for Mental Health Systems

To support architecture decision-making in small and medium-sized enterprises (SMEs) delivering mental health services, this study proposes a transparent, single-equation scoring model that integrates operational performance, economic feasibility, and risk exposure into a unified metric.

Let $\mathcal{A} = \{A_1, A_2, \ldots, A_J\}$ denote the set of candidate software architecture options for the mental health system. For each architecture option A_j, a set of measurable Key Performance Indicators (KPIs) is evaluated, such as system availability, patient response time, therapy adherence rates, and infrastructure cost.

Each KPI is normalized to a unitless score $s_i(j) \in [0, 1]$, where higher values indicate better performance. Cost-oriented KPIs are inverted during normalization to ensure all KPI scores follow a *"higher is better"* convention.

The overall *Architecture–Economics Alignment Score (AEAS)* for architecture option A_j is defined as:

$$\text{AEAS}(j) = \left(\sum_{i=1}^{p} w_i \cdot s_i(j) \right) \cdot \left(\frac{B_{\max}}{C_{\text{build}}(j)} \right) \cdot (1 - \gamma \cdot R(j)) \tag{6.1}$$

subject to:

$$\sum_{i=1}^{p} w_i = 1, \quad 0 \leq s_i(j),\ R(j),\ \gamma \leq 1 \tag{6.2}$$

Explanation of Terms:

- $s_i(j)$: Normalized performance score of KPI i for architecture option A_j (e.g., patient wait time, system uptime, therapy adherence)
- w_i: Priority weight assigned to KPI i based on organizational goals
- $B_{\max}$: Maximum affordable implementation budget for the SME mental health system
- $C_{\text{build}}(j)$: One-time build or migration cost of architecture A_j
- $R(j)$: Normalized operational risk score of architecture A_j (e.g., data breaches, downtime, regulatory compliance risk)
- γ: Risk sensitivity factor, where higher values indicate lower tolerance for risk

Equation (1) aggregates performance, economic, and risk considerations into a single metric. The weighted KPI sum captures alignment across patient outcomes and operational performance, the cost ratio reflects economic feasibility, and the risk factor penalizes architectures with higher operational or compliance risk.

The model's constraints in equation (2) ensure that KPI weights sum to one and that all normalized scores and risk measures remain within the unit interval [0,1], supporting interpretability and computational stability.

Decision Rule:

The preferred architecture is selected by maximizing the AEAS value:

$$A^* = \arg\max_{A_j \in \mathcal{A}} \text{AEAS}(j) \tag{6.3}$$

Interpretation:

- The first term captures overall operational and clinical performance.
- The second term penalizes architectures that exceed SME budget constraints.
- The third term reduces the score for architectures with higher operational or compliance risk.

The decision rule in equation (3) selects the architecture that maximizes the AEAS across all alternatives, producing an intuitive, comparable score that can be computed with simple spreadsheet or lightweight analytical tools.

Why This Model Is Suitable for SME Mental Health Systems

This model is particularly well-suited for SMEs implementing AI-driven mental health systems due to its methodological simplicity and contextual practicality. It operationalizes evaluation through a single composite equation with a limited set of input variables, relying on basic KPIs and cost estimates that are realistically obtainable within resource-constrained healthcare environments. The formulation produces a unified and interpretable score, thereby enabling informed decision-making without the need for advanced analytical infrastructure or specialized expertise. Importantly, the model integrates multiple critical dimensions—clinical effectiveness, economic feasibility, and operational risk—within a single evaluative framework. This integrated approach supports balanced trade-off analysis, allowing SMEs to align system design and deployment decisions with both healthcare outcomes and sustainability constraints. Consequently, the model provides a pragmatic yet theoretically grounded mechanism for optimizing AI-enabled mental health solutions in low-resource and SME contexts.

6.4 Architectural Decisions and Economic Considerations

Architectural decisions within the proposed system are explicitly guided by economic considerations relevant to low-resource environments. Modularity reduces change propagation and maintenance effort, thereby lowering long-term operational costs. Service-oriented decomposition allows components to be deployed and scaled independently, improving cost elasticity and enabling pay-as-you-grow infrastructure models, as illustrated in Table 6.1.

The selective use of cloud resources balances scalability with affordability by offloading computationally intensive AI inference tasks to cloud services while minimizing persistent infrastructure costs. Lightweight application services and efficient data management strategies reduce bandwidth and storage expenses. Architectural simplicity further enhances maintainability, lowering staffing and training costs, as demonstrated in Table 6.2.

6.5 Summary

This chapter presented a comprehensive analysis of software architecture and economic considerations for AI-driven systems in low-resource healthcare contexts. By synthesizing prior research and addressing identified gaps, the chapter established architecture as a strategic bridge between governance objectives and system-level execution. The proposed modular architecture demonstrates how technical design choices can simultaneously support scalability, reliability, ethical compliance, and economic sustainability. While this chapter focused on architectural structure and economic rationale, architectural soundness alone does not guarantee system reliability or trustworthiness in safety-critical healthcare applications. Accordingly, the following chapter focuses on quality assurance and testing strategies employed to validate system correctness, robustness, and ethical reliability.

Table 6.1: SME Architecture Features and Their Economic Impact

Stage	How It Helps SMEs	Economic Connection / Metric
Modularity	Decomposes the system into independent components, reducing complexity and simplifying maintenance and updates.	Minimizes change propagation, reduces maintenance costs, and improves total cost of ownership (TCO).
Service-Oriented Decomposition	Enables independent deployment and scaling of system components based on demand and usage patterns.	Supports cost elasticity through pay-as-you-grow models, optimizing infrastructure utilization and operational expenditure (OPEX).
Impact Mapping	Clarifies how each feature or architectural choice enhances customer satisfaction, scalability, and differentiation.	Links architecture directly to ROI, customer retention, and revenue growth.
KPI Integration	Connects system performance metrics to profitability, preventing overengineering.	Establishes measurable relationships between total cost of ownership (TCO), payback period, and operational efficiency.
AI Recommendation Engine	Automates architectural analysis, reducing dependence on costly consultants and trial-and-error design.	Reduces design costs and accelerates product launch timelines.
Economic Simulation	Predicts long-term maintenance costs and scalability requirements before committing capital.	Improves financial predictability and risk-adjusted return on investment (ROI).
Performance Dashboard	Enables executives and non-technical stakeholders to monitor architecture's effect on operational outcomes.	Supports continuous tracking of operational expenditure (OPEX) relative to performance gains.
Feedback & Learning Loop	Ensures lessons from one project inform future initiatives, enhancing efficiency and innovation.	Drives sustained cost reductions and maximizes innovation return on investment across the product lifecycle.

Table 6.2: Sequential Architecture Process and Component Mapping for a Mental Health System

Stage	Component	Description	Purpose
1	**Business Context** – Impact Mapping	Identify organizational goals, mental health program objectives, and KPIs such as patient satisfaction, therapy adherence, and engagement levels. Map how software architecture contributes to these outcomes.	Ensures all architectural decisions align with mental health priorities and patient care objectives from the start.
2	**Economic Linkage** – KPI Integration	Translate architectural attributes (e.g., scalability, maintainability, data security) into measurable system and health outcomes, such as treatment completion rates, response time, and operational cost.	Builds a quantifiable link between technical design and both clinical and economic performance.
3	**Design Exploration** – AI Recommendation Engine	Leverage AI to analyze historical patient data and system performance, simulate trade-offs, and recommend architecture patterns that optimize patient outcomes and cost efficiency.	Accelerates decision-making while minimizing design errors and supporting evidence-based mental health interventions.
4	**Scenario Evaluation** – Economic Simulation Module	Model multiple "what-if" scenarios (e.g., teletherapy vs. in-person vs. hybrid delivery) to predict cost, system performance, and patient outcomes under different operational conditions.	Enables evidence-based investment decisions for scalable and sustainable mental health services.
5	**Governance** – Performance Dashboard	Continuously monitor operational KPIs (system uptime, throughput, security) alongside clinical KPIs (patient engagement, therapy completion rates, satisfaction).	Provides real-time visibility into the impact of architecture decisions on both clinical outcomes and cost efficiency.
6	**Continuous Feedback** – Feedback & Learning Loop	Collect real-world system and patient data from deployed mental health applications and feed insights back into architecture and service improvement.	Supports continuous improvement, learning, and long-term growth of mental health service delivery.

7 Quality Assurance & AI-Based Testing

7.1 Introduction

Quality Assurance (QA) plays a critical role in ensuring that software systems meet functional requirements, maintain reliability, and remain sustainable throughout their lifecycle. This role becomes particularly significant in AI-driven systems, where system behavior is inherently dynamic, data-dependent, and often non-deterministic.

In the context of AI-based mental health systems, quality assurance extends beyond traditional correctness verification to include considerations of reliability, robustness, fairness, and ethical responsibility. Errors in such systems may lead to incorrect screening outcomes, delayed interventions, or reduced user trust, making QA a fundamental requirement rather than a supporting activity.

For small and medium-sized enterprises (SMEs) operating in low-resource environments, conventional QA practices are often constrained by limited expertise, infrastructure, and financial capacity. These constraints necessitate approaches that are both efficient and scalable. AI-based testing offers a promising solution by enabling automation, adaptive validation, and intelligent prioritization of testing efforts.

Building on the literature discussed in Chapter 2, this chapter focuses on the *application* of AI-based testing within the proposed Software Architecture–Economics Alignment Framework (SAEAF). It introduces a conceptual QA pipeline tailored for AI-driven mental health systems and demonstrates how quality assurance is integrated into governance and architectural decision-making.

7.2 QA Requirements for AI-Driven Mental Health Systems

AI-enabled mental health systems introduce unique quality assurance requirements that extend beyond traditional software validation. These systems must ensure not only functional correctness but also stability under evolving data conditions, consistency of AI outputs, and alignment with ethical and clinical expectations.

Key QA requirements in this context include:

- **Reliability and Stability:** Ensuring consistent system performance under varying usage and data conditions.

- **Model Robustness:** Validating system behavior under data drift, incomplete inputs, and noisy datasets.
- **Fairness and Bias Mitigation:** Detecting and minimizing biases in mental health screening outputs.
- **Explainability and Transparency:** Supporting interpretability of AI-generated recommendations.
- **Operational Continuity:** Maintaining system availability and responsiveness in low-resource environments.

These requirements establish the need for a continuous and adaptive QA approach that integrates both traditional testing practices and AI-based validation techniques.

7.3 Conceptual QA Pipeline for AI-Driven Mental Health Systems

To operationalize quality assurance within the proposed framework, this research introduces a conceptual QA pipeline that integrates AI-based testing with governance and economic considerations.

Figure 8 presents the overall structure of the proposed pipeline.

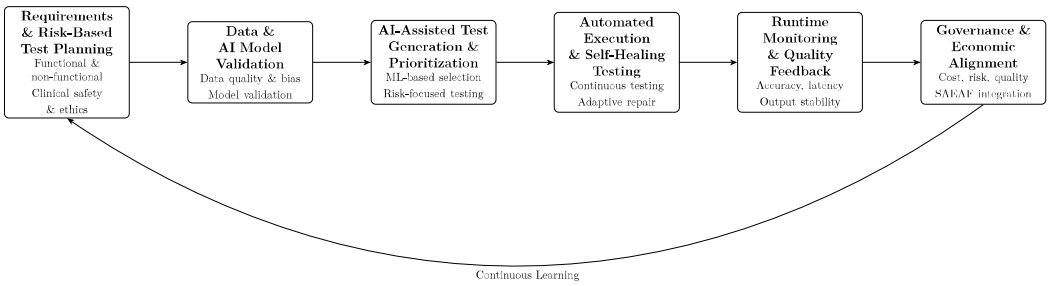


Figure 8: Conceptual Quality Assurance Pipeline for AI-Driven Mental Health Systems

The pipeline consists of six interrelated stages:

7.3.1 Requirements and Risk-Based Test Planning

Quality assurance begins with translating functional, non-functional, and ethical requirements into test objectives. In mental health systems, this includes clinical safety constraints, fairness considerations, and user protection requirements.

7.3.2 Data and Model Validation

Given the data-driven nature of AI systems, validating input data quality and model assumptions is essential. This stage ensures that datasets are representative, unbiased, and suitable for reliable inference.

7.3.3 AI-Assisted Test Generation and Prioritization

Machine learning techniques are used to generate and prioritize test cases based on system criticality, historical failures, and risk exposure. This enables efficient allocation of testing resources in SME environments.

7.3.4 Automated Execution and Self-Healing Testing

Test cases are executed continuously across system configurations. Self-healing mechanisms adapt test scripts to interface or workflow changes, reducing maintenance overhead.

7.3.5 Runtime Monitoring and Feedback

Post-deployment monitoring captures operational metrics such as system performance, error rates, and AI output consistency. These metrics provide insights into real-world system behavior.

7.3.6 Governance and Economic Alignment

QA outcomes are integrated into governance processes and economic evaluation within SAEAF. Quality metrics directly influence cost, risk, and performance assessments, enabling informed architectural decisions.

7.4 Integration with the SAEAF Framework

Within the proposed SAEAF framework, quality assurance functions as a continuous governance mechanism rather than a standalone activity.

Outputs from the QA pipeline—such as reliability indicators, defect rates, and performance metrics—feed into the Architecture–Economics Alignment Score (AEAS). This integration ensures that architectural decisions are informed not only by technical feasibility but also by quality, risk exposure, and economic sustainability.

By linking QA outcomes with economic indicators such as operational cost and risk-adjusted performance, the framework enables SMEs to balance quality assurance investments with financial constraints. This is particularly important in low-resource environments, where inefficient testing strategies can lead to unsustainable costs.

7.5 Summary

This chapter presented a structured approach to quality assurance for AI-driven mental health systems, emphasizing the integration of AI-based testing within the SAEAF framework. A conceptual QA pipeline was proposed to support continuous validation across the system lifecycle, combining risk-based planning, AI-assisted testing, automated execution, and governance feedback.

Unlike traditional approaches, the proposed model positions quality assurance as a continuous and economically informed process that directly influences architectural decision-making. This alignment ensures that AI-based mental health systems remain reliable, scalable, and sustainable within SME and low-resource contexts.

The following chapter extends this discussion by examining cloud deployment and operational strategies, focusing on how infrastructure decisions further impact system performance, cost efficiency, and long-term sustainability.

8 Cloud Deployment & Operations

8.1 Introduction

The deployment of AI-driven mental health platforms requires an operational environment that is scalable, secure, and resilient while remaining economically viable in low-resource contexts. Within the SAEAF framework, the Cloud Deployment & Operations layer operationalizes architectural decisions through concrete infrastructure mechanisms such as auto-scaling, network isolation, monitoring, and continuous delivery pipelines. This chapter presents a deployment model that aligns AI inference workloads, sensitive health data governance, and cost constraints typical in Bangladesh and comparable regions.

The proposed approach integrates three dimensions:

- **Scalable AI service hosting**,
- **Secure health data management**, and
- **Operational governance with cost controls.**

These dimensions ensure that the platform can support variable screening demand, maintain confidentiality of DASS-21 responses, and operate sustainably within institutional budgets.

8.2 Deployment Requirements for AI-Driven Mental Health Systems

AI-based screening platforms differ from conventional web systems due to their mixed workload profile—combining low-latency user interactions with compute-intensive model inference. From the SAEAF perspective, deployment must satisfy:

- **Elastic inference capability** for NLP and risk-scoring models;
- **Data locality and privacy** for culturally sensitive mental-health records;
- **High availability** to support continuous self-screening services;
- **Auditability** for clinical governance and research validation;
- **Cost predictability** for public and NGO-led healthcare programs.

These requirements motivate a cloud-native architecture built on Virtual Private Cloud segmentation, managed identity controls, and horizontally scalable compute services.

8.3 Proposed Cloud Deployment Architecture

8.3.1 Network and Security Design

The deployment adopts a multi-tier architecture with strict separation between public interaction layers and protected clinical services. A dedicated **Virtual Private Cloud (VPC)**, Figure 9 hosts two subnet classes:

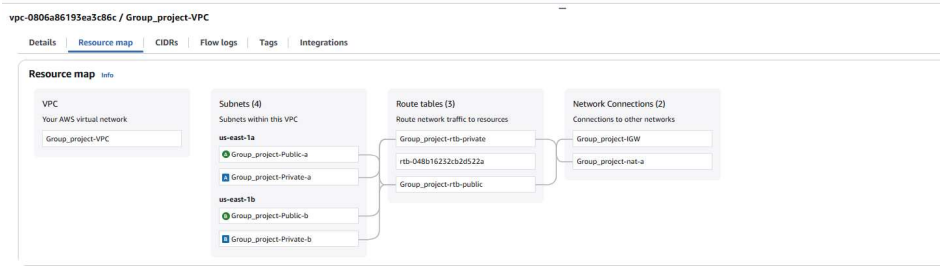


Figure 9: Virtual Private Cloud Architecture

- **Public Subnet:** Contains load balancers and API gateways that handle user requests for DASS-21 screening. This layer is exposed to the internet but protected by Web Application Firewalls (WAF) and rate-limiting controls.
- **Private Subnet:** Hosts AI inference services, databases, and administrative tools. This layer is isolated from direct internet access, with communication only allowed through secure API endpoints and VPN connections for authorized personnel.

Outbound access from private zones is mediated through a NAT gateway, while inbound traffic is controlled through security groups and Network ACLs, Figure 10. This model mirrors proven cloud isolation strategies used in prior AWS-based systems and ensures compliance with healthcare confidentiality principles.

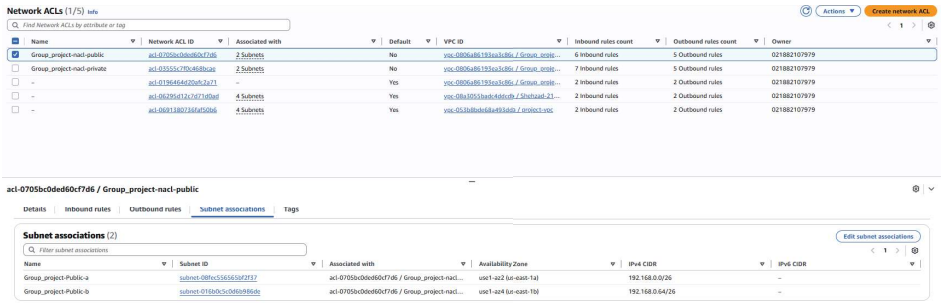


Figure 10: Network Access Control List (ACL)

Figure 11 illustrates the logical deployment topology, where user requests traverse an Application Load Balancer before reaching containerized AI services. Patient responses are stored only within private subnets using encrypted storage.

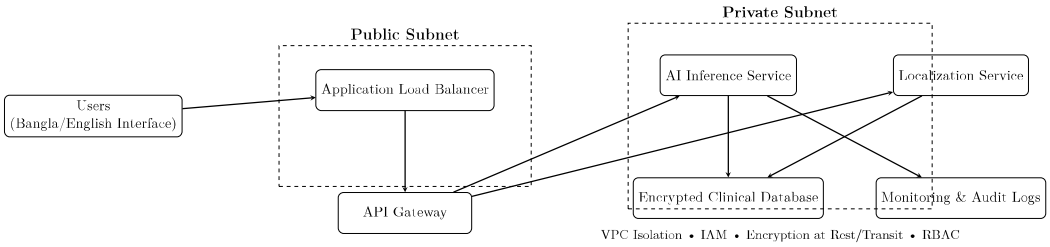


Figure 11: Cloud Deployment Topology for the AI-Driven Mental Health Platform

8.3.2 Application Runtime Environment

The framework employs virtualized compute (EC2) instances to host the main application logic and processing pipelines. These instances provide an isolated execution environment for business rules, data preprocessing routines, and integration services. The architecture separates the web interface, background processing, and AI inference tasks to prevent resource contention and to enable independent scaling. Such decomposition allows compute resources to be provisioned based on workload characteristics rather than as a monolithic server. Containerized services are used to encapsulate dependencies and runtime configurations, ensuring portability across development, testing, and production environments. The application layer exposes RESTful endpoints consumed by client applications and internal microservices. This approach aligns with cloud-native best practices by promoting loose coupling and stateless service design.

8.3.3 Auto-Scaling and Elastic Resource Management

To accommodate variable workloads, the Compute Layer implements dynamic scaling policies as depicted in Figure 12. Horizontal scaling groups monitor CPU utilization, request latency, and queue depth to determine when additional instances should be launched or terminated. This elasticity ensures that peak demand—such as simultaneous screening requests—does not degrade system responsiveness.

Serverless functions are utilized for lightweight tasks including notification dispatch, data transformation, and periodic health checks. By combining long-running virtual machines with event-driven functions, the architecture achieves cost efficiency while preserving low-latency processing for critical operations.

8.4 Monitoring, Logging, and Governance

Comprehensive observability is embedded within the layer through centralized logging and metrics collection. Each service emits operational telemetry covering request rates, error counts, and execution time. These metrics feed into dashboards and alerting rules that support proactive maintenance and incident re-

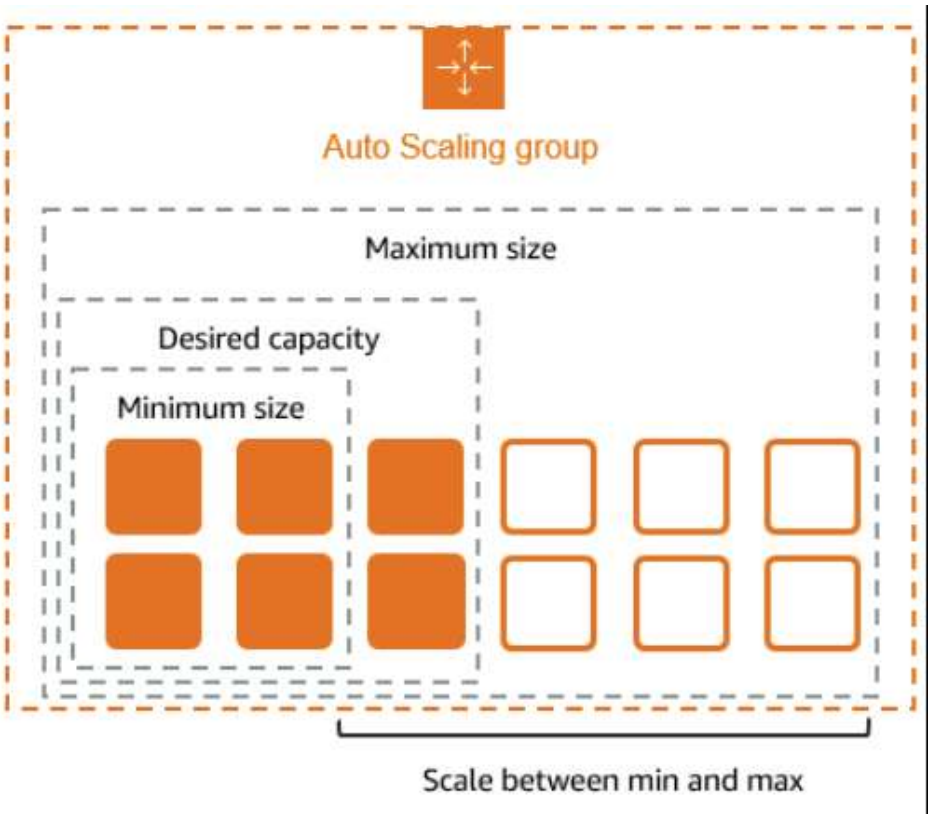


Figure 12: Auto-Scaling EC2 Instances

sponse. Tracing mechanisms correlate user requests with downstream AI computations, enabling end-to-end visibility of the decision pipeline. Such transparency is particularly important for clinical and mental-health applications where explainability and accountability are required.

8.5 Security and Isolation

The Compute Layer operates inside a private network boundary with strict identity and access management. Service roles enforce least-privilege access to storage, model repositories, and messaging services. All inter-service communication occurs over encrypted channels, and secrets are managed through a dedicated credential vault. These controls ensure compliance with healthcare data protection principles while supporting multi-tenant operation.

8.6 Summary

This chapter presented the Cloud Deployment & Operations layer of the proposed framework, detailing how architectural decisions are operationalized through concrete infrastructure mechanisms. The deployment model adopts a Virtual Private Cloud–based architecture with segmented public and private subnets, Application Load Balancer–mediated access, and EC2 compute instances managed via

Auto Scaling Groups. Together, these components provide elasticity, fault tolerance, and controlled network isolation required for hosting AI-enabled services in resource-constrained environments.

The operational design separates user-facing interfaces from processing and inference workloads, enabling independent scaling and minimizing resource contention. CloudWatch-based monitoring and telemetry introduce observability across the service lifecycle, supporting proactive incident management and performance governance. The reliance on on-demand resource provisioning reflects an economically pragmatic approach, aligning infrastructure costs with actual usage patterns—an essential requirement for public and NGO-led mental-health initiatives in Bangladesh.

Although the reference implementation originated in a financial analytics context, the underlying deployment principles—elastic compute, secure network segmentation, load-balanced service exposure, and centralized monitoring—are directly transferable to AI-driven mental-health screening platforms. These mechanisms provide the infrastructural foundation necessary for hosting multilingual NLP models, risk-scoring services, and confidential DASS-21 data processing in a reliable and cost-aware manner.

Having established the governance model, architectural design, and operational deployment strategy, the following chapter moves to Evaluation & Discussion, where the proposed framework is assessed in terms of usability, performance, ethical compliance, and feasibility within the Bangladeshi healthcare context.

9 Evaluation & Discussion

9.1 Evaluation Strategy and Design Science Positioning

As described in Section 3.2.5, this research follows the Design Science Research (DSR) evaluation approach to assess the proposed artifact. Within the DSR paradigm, evaluation focuses on determining whether the designed artifact effectively addresses the identified problem and satisfies the defined objectives.

Since the proposed SAEAF-based AI-assisted mental health screening architecture has not yet undergone full real-world deployment, the evaluation presented in this chapter adopts an ex-ante analytical and scenario-based assessment approach.

Accordingly, the evaluation examines several dimensions of the artifact, including:

- Problem–solution alignment
- Architectural feasibility under representative usage scenarios
- Economic sustainability within low-resource healthcare environments
- Governance and ethical suitability
- Scalability and deployment considerations

It is important to emphasize that this evaluation does not claim clinical validation, AI performance benchmarking, or large-scale usability testing. Instead, the purpose of this chapter is to assess whether the proposed architecture is conceptually sound, contextually appropriate, and operationally feasible within the target environment of Bangladesh.

9.2 Need for the Application: Evidence from Mental Health Context

The necessity of the proposed bilingual and culturally adaptive mental health screening system is strongly supported by empirical findings obtained during the requirement engineering and pre-user validation phases described in Chapter 4.

As discussed in Section 4.X, an initial bilingual DASS-21 survey was conducted using a Google Forms-based implementation containing all 21 DASS-21 items

presented in both English and Bangla. The survey collected responses from approximately 150 participants consisting primarily of students, young adults, and working individuals familiar with digital platforms. The survey was conducted online to evaluate linguistic accessibility, cultural appropriateness, usability, and overall user interaction patterns.

The statistical distributions and graphical analyses presented in this chapter are derived from that initial survey dataset and are used here to evaluate the contextual relevance and problem–solution alignment of the proposed artifact within the Design Science Research (DSR) evaluation framework.

The analysis was conducted using the Depression Anxiety Stress Scales (DASS-21), a widely used psychological screening instrument that measures symptoms associated with depression, anxiety, and stress. The results suggest the presence of notable depression, anxiety, and stress indicators across multiple demographic groups within the surveyed population.

Figures 13, 14 and 15 illustrate the distribution of DASS-21 scores across age groups, occupational categories, and gender–income segments. The results demonstrate that mental health challenges are not restricted to a single demographic group but appear across diverse segments of the population. Younger individuals and students showed particularly high levels of reported stress and anxiety, while working professionals displayed elevated levels of depressive symptoms in several cases.

Despite this prevalence, the existing mental health service infrastructure in Bangladesh remains limited. Services are heavily concentrated in urban centers, and many individuals face barriers such as social stigma, lack of awareness, limited availability of trained professionals, and linguistic barriers in accessing mental health resources. As a result, many individuals experiencing symptoms of psychological distress do not seek professional help until conditions become severe.

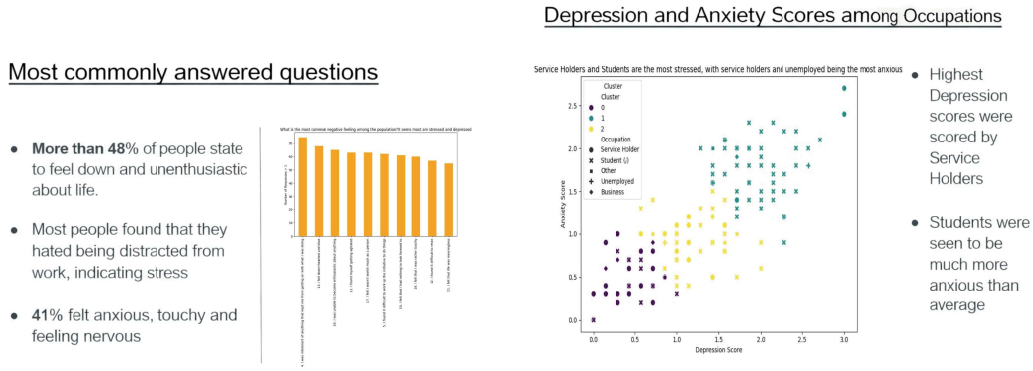
The requirement gathering analysis further revealed several key expectations from potential users. Participants expressed a preference for private and trustworthy self-screening tools that allow individuals to assess their mental health status without immediate clinical interaction. The importance of Bangla language interaction was also strongly emphasized, as many users reported discomfort with English-only digital health platforms. Additionally, participants indicated a need for explanations that are culturally sensitive and easily understandable rather than relying on technical psychological terminology.

These findings collectively demonstrate the contextual relevance of the proposed system. The SAEAF-based architecture directly addresses these requirements by incorporating bilingual interaction mechanisms, modular screening components, AI-assisted explanation capabilities, and scalable cloud-based infrastructure. From a Design Science Research perspective, these results confirm that the proposed artifact satisfies the problem–solution alignment criterion.

The collected survey data revealed noticeable variations in reported depression, anxiety, and stress indicators across demographic and socio-economic categories. The following figures summarize the observed distribution patterns derived from the bilingual DASS-21 survey responses.



Figure 13: Age-wise distribution of DASS-21 depression, anxiety, and stress scores obtained from the bilingual pre-validation survey



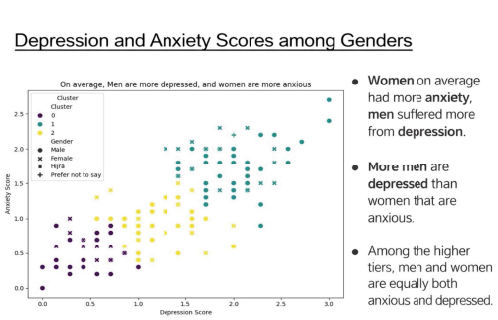
(a) Distribution of DASS-21 Scores by Population Group

(b) Distribution of DASS-21 Scores by Occupation

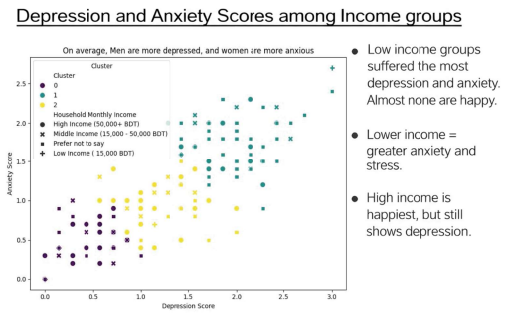
Figure 14: Distribution of DASS-21 indicators across population categories and occupational groups from the pre-validation survey dataset

9.3 Evaluation of Agile Governance in Distributed Development Teams

Traditional Agile methodologies emphasize flexibility, rapid iteration, and adaptive development practices. While these characteristics are highly valuable in general software engineering contexts, they may be insufficient for systems operating within safety-sensitive domains such as mental health technology. In such environments, additional governance mechanisms are required to ensure compliance with ethical standards, data protection requirements, and responsible AI development practices.



(a) Distribution of DASS-21 Scores by Gender



(b) Distribution of DASS-21 Scores by Income

Figure 15: Distribution of DASS-21 depression, anxiety, and stress indicators across gender and income groups

The proposed integration of Agile Governance mechanisms aims to address these limitations by introducing structured oversight within the Agile development process. This approach maintains the iterative advantages of Agile development while incorporating governance structures that improve traceability, documentation, and compliance readiness. In distributed development teams, such mechanisms also reduce ambiguity in interpreting system requirements, particularly when implementing culturally sensitive screening logic such as the DASS-21 assessment model.

From an analytical perspective, the introduction of governance elements such as structured backlogs, traceable user stories, and compliance checkpoints improves requirement stability without eliminating development flexibility. Clear documentation standards and defined team roles also contribute to improved communication and coordination among geographically distributed development teams. These measures reduce the risk of inconsistent interpretation of psychological assessment logic, especially when bilingual interfaces and culturally adapted explanations are implemented.

Furthermore, the governance layer introduces mechanisms for ethical oversight, including bias review procedures, consent management protocols, and explainability checkpoints for AI-assisted components. These safeguards are generally absent in conventional Scrum implementations but are essential for AI-enabled healthcare systems. The evaluation presented here is analytical rather than experimental; however, it demonstrates that Agile Governance integration provides a structurally suitable framework for managing development risks in safety-sensitive digital health applications.

9.4 Hybrid Project Management Contribution

The development of AI-assisted mental health screening systems involves characteristics of both innovative software engineering projects and regulated healthcare technology initiatives. Purely Agile approaches may introduce excessive scope volatility in such contexts, while traditional Waterfall methodologies can limit the flexibility required for iterative refinement of AI-driven components and user

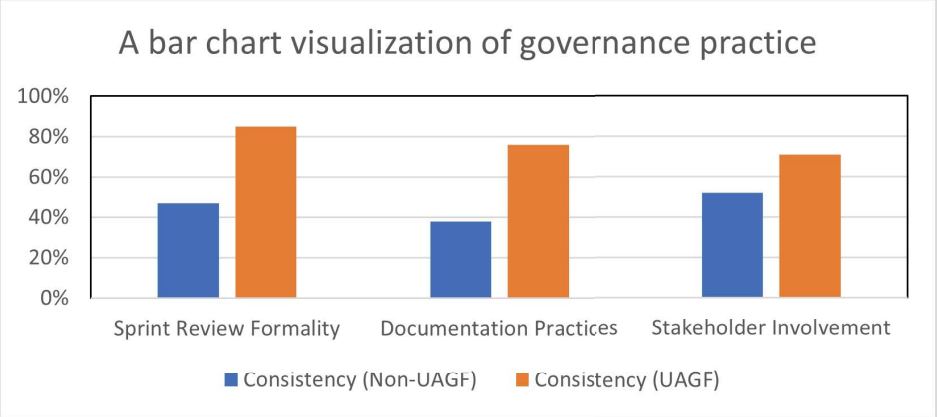


Figure 16: Impact of Agile Governance Practices on Distributed Team Performance

interfaces.

To address this challenge, the proposed framework adopts a hybrid project management approach that combines elements of both Agile and structured development models. Within this hybrid structure, governance artifacts typically associated with structured methodologies—such as risk registers, compliance documentation, and validation checkpoints—are integrated with Agile development cycles. This combination enables controlled system evolution while preserving the benefits of iterative development.

Agile iterations are particularly valuable for tasks such as Bangla language natural language processing refinement, user interface localization, and adaptive explanation improvements. At the same time, stage-gate review mechanisms provide decision points where system risks, ethical compliance, and architectural consistency can be evaluated before further development progresses.

Analytical evaluation suggests that this hybrid model supports balanced development progress across technical innovation, cultural adaptation, and regulatory compliance. By combining structured governance with iterative development cycles, the hybrid approach improves project predictability while maintaining the flexibility necessary for AI-driven software systems.

9.5 Economic Impact of SAEAF Architecture

The Software Architecture–Economic Alignment Framework (SAEAF) plays a central role in ensuring that the proposed mental health screening system remains economically sustainable within low-resource environments. The architectural design emphasizes modularity, maintainability, and resource efficiency, all of which contribute to reducing the long-term total cost of ownership.

A modular architecture enables different system components—including the screening engine, explanation module, and clinician portal—to evolve independently. This separation allows updates to be implemented without requiring full system redesign or redeployment. For example, linguistic resources related to Bangla interaction can be refined independently from the core scoring logic of the

DASS-21 screening model. Such modular separation reduces maintenance complexity and supports incremental system improvements.

The architecture also encourages component reusability across different deployment contexts. Institutions such as universities, non-governmental organizations, and telemedicine providers can adapt the framework to their specific operational environments. This flexibility increases the long-term return on investment by enabling the architecture to support multiple mental health service providers.

From a risk management perspective, the architectural separation between clinical scoring logic and experimental AI modules provides an additional layer of protection. By isolating validated psychological assessment components from adaptive AI features, the system reduces potential liability risks and ensures that experimental components cannot directly compromise the integrity of screening results.

Overall, the architectural design demonstrates strong alignment between technical structure and long-term operational constraints within the Bangladeshi healthcare ecosystem.

9.6 Advantages of AI-Based Testing

Ensuring the reliability of AI-assisted health applications requires robust software testing strategies capable of adapting to rapid development cycles. AI-based testing approaches provide several advantages in this context, particularly when systems evolve through frequent interface updates and language refinements.

Automated regression testing plays an essential role in validating the correct implementation of DASS-21 scoring logic. Because the screening algorithm relies on precise score calculations, automated tests help prevent accidental modifications that could lead to incorrect mental health assessments. This capability is especially important when multiple developers contribute to the codebase over extended development cycles.

Self-healing testing frameworks further reduce maintenance overhead by automatically adapting test cases when interface elements change. This feature is particularly beneficial for bilingual applications in which user interface components may evolve during localization and language refinement processes.

Visual AI testing techniques also improve system compatibility across different device types, including low-end smartphones commonly used in developing regions. By verifying interface rendering and readability, visual testing helps ensure that the application remains accessible to a broad range of users.

From an analytical perspective, AI-driven testing strategies contribute to improved software reliability, reduced quality assurance costs, and greater confidence in system updates during iterative development.

9.7 Cloud IaaS Deployment Economics

Deploying nationwide digital mental health infrastructure requires significant computational resources and operational flexibility. Traditional on-premise infrastructure models would require substantial initial capital investment and ongoing main-

tenance costs, making them impractical for large-scale deployment in low-resource environments.

Cloud-based Infrastructure-as-a-Service (IaaS) platforms offer an economically viable alternative. Elastic resource scaling allows the system to adapt to fluctuations in user demand without permanent infrastructure expansion. For example, screening activity may increase during awareness campaigns or public health initiatives, and cloud platforms can dynamically allocate additional computational resources during such periods.

The pay-as-you-go pricing model further aligns operational expenses with actual system usage, reducing financial risk during early deployment phases. In addition, cloud platforms provide integrated security, backup, and disaster recovery mechanisms that would otherwise require significant technical expertise to implement independently.

These characteristics make cloud-based deployment particularly suitable for the proposed mental health screening architecture, as they support nationwide accessibility while minimizing upfront infrastructure costs and operational complexity.

9.8 Overall Discussion and Research Question Alignment

The evaluation results collectively indicate that the proposed artifact provides a feasible architectural solution for scalable mental health screening within the Bangladeshi context. The system design demonstrates that culturally adaptive and bilingual screening platforms can be developed using the SAEAF architectural framework while maintaining economic sustainability and governance oversight.

In relation to the research questions, the evaluation confirms that a culturally adaptive AI-assisted screening system can be architecturally designed using the SAEAF framework. Furthermore, the analysis shows that economic sustainability can be supported through modular architecture, cloud deployment strategies, and hybrid governance models. Finally, the integration of governance mechanisms enhances development traceability, ethical oversight, and risk visibility within distributed software engineering environments.

It is important to emphasize that the proposed artifact does not claim clinical diagnostic authority or superior AI model performance. Instead, the research contributes a structured architectural framework designed to support scalable mental health screening while aligning technical design decisions with economic and governance considerations.

While the proposed SAEAF-based framework has been evaluated primarily through analytical, architectural, and scenario-based assessment within the Design Science Research (DSR) paradigm, the findings demonstrate that the framework provides a structured and contextually appropriate foundation for developing AI-driven mental health systems in low-resource environments. The evaluation confirms that the proposed architecture successfully integrates bilingual accessibility, culturally adaptive interaction, governance-oriented development practices, AI-based quality assurance, and scalable cloud deployment considerations into a unified software engineering approach.

The current study focuses primarily on architectural design, governance integration, and operational feasibility rather than large-scale clinical deployment or AI model optimization. Consequently, the evaluation emphasizes conceptual validity, contextual suitability, and system-level feasibility within the Bangladeshi context. Similarly, while the economic assessment presented in this research is qualitative in nature, it demonstrates how architectural alignment, governance mechanisms, and scalable deployment strategies can support sustainable implementation for small and medium-sized organizations operating under infrastructural and financial constraints.

Despite these boundaries, the proposed framework offers several practical contributions. First, it provides a reproducible software engineering methodology for designing culturally adaptive AI-enabled healthcare systems in multilingual and resource-constrained environments. Second, the integration of the Unified Agile Governance Framework (UAGF) with the Software Architecture and Economics Alignment Framework (SAEAF) establishes a governance-aware and economically conscious development approach that extends beyond conventional AI system design methodologies. Third, the bilingual and human-centered design strategy directly addresses accessibility and usability challenges frequently overlooked in existing AI healthcare platforms targeting developing regions.

The framework therefore serves not only as a conceptual architecture for AI-assisted mental health screening, but also as a scalable foundation for future AI-driven healthcare applications requiring governance, adaptability, and sustainable deployment in low-resource contexts. Future work may extend this research through real-world deployment, longitudinal usability studies, quantitative economic modeling, and broader empirical validation across diverse demographic populations.

10 Conclusion & Future Work

10.1 Conclusion

This research investigated how a culturally adaptive, AI-assisted mental health screening system could be designed and deployed in a sustainable and contextually appropriate manner within Bangladesh. The study combined empirical mental health evidence, human-centered artificial intelligence principles, and software engineering methodologies to develop and evaluate a conceptual system architecture based on the Software Architecture–Economic Alignment Framework (SAEAF).

The findings of this research highlight the strong societal necessity for accessible mental health screening solutions. Empirical evidence obtained through the DASS-21 requirement gathering study indicates a considerable prevalence of symptoms related to depression, anxiety, and stress among Bangladeshi users. Despite this demand, access to mental health services remains limited due to social stigma, shortages of trained professionals, and geographic concentration of services in urban areas. These factors demonstrate the importance of scalable digital solutions that allow individuals to conduct preliminary self-screening in a private and accessible manner.

The research further demonstrates that human-centered design principles are essential for the adoption of AI-assisted mental health technologies. User trust, explainability, and culturally appropriate language adaptation emerged as critical determinants of system acceptance. In particular, bilingual interaction and culturally sensitive explanations are necessary to ensure that users understand screening outcomes and feel comfortable engaging with digital mental health tools.

Another important conclusion concerns the role of development processes in responsible AI deployment. The study shows that technical innovation alone is insufficient when designing AI systems for healthcare contexts. The integration of Agile governance mechanisms and hybrid project management structures enables development teams to balance flexibility with ethical oversight and regulatory awareness. Such governance mechanisms are particularly valuable when multiple stakeholders, including software engineers, clinicians, and policymakers, are involved in system development.

From an architectural perspective, the proposed SAEAF framework demonstrates that software architecture decisions can significantly influence the economic sustainability of digital health systems. By emphasizing modular design, component separation, and scalable infrastructure, the architecture reduces long-term maintenance costs and supports reuse across multiple organizational contexts such as universities, non-governmental organizations, and telemedicine platforms. This alignment between architectural design and economic considerations contributes

to improved long-term sustainability.

Quality assurance also plays a crucial role in the reliability of AI-assisted mental health applications. The study highlights the potential of AI-based testing strategies to maintain system integrity during rapid development cycles. Automated regression testing ensures the correctness of screening logic, while intelligent testing approaches help maintain system stability as multilingual interfaces and AI-assisted components evolve.

Finally, the research identifies cloud-based infrastructure as a key enabler for equitable access to digital mental health services. Elastic cloud deployment allows the system to scale dynamically in response to user demand while minimizing infrastructure investment. This approach is particularly appropriate for low-resource environments such as Bangladesh, where traditional on-premise infrastructure would be economically impractical.

Overall, the results demonstrate that responsible software engineering practices can transform conceptual AI research into a practical framework for addressing real-world public health challenges. The proposed architecture does not attempt to replace clinical diagnosis but instead provides a structured and scalable screening framework that can support early identification of mental health risks and encourage professional consultation.

10.2 Future Work

Although this research provides a conceptual architectural framework for AI-assisted mental health screening, several opportunities remain for future investigation and practical implementation.

One important direction for future work involves clinical validation of the proposed screening system. Longitudinal studies could be conducted to compare screening recommendations generated by the system with assessments provided by licensed mental health professionals. Such studies would help evaluate the practical effectiveness of the screening tool and identify opportunities for refinement. In addition, collaboration with healthcare institutions could enable the evaluation of protocols for identifying high-risk users and facilitating appropriate referral pathways.

Another promising area for further research involves advanced personalization mechanisms. Future system versions could incorporate adaptive dialogue models that respond to regional linguistic variations and dialects within the Bangla language. Voice-based interaction technologies may also improve accessibility for users with limited literacy or limited experience using text-based digital interfaces.

Economic evaluation represents another important direction for future work. While this study provides qualitative reasoning regarding economic sustainability, future research could conduct detailed total cost of ownership and return-on-investment analyses across different deployment contexts. Such studies could provide valuable insights for organizations such as universities, non-governmental organizations, and government agencies considering large-scale adoption of digital mental health screening platforms.

Future research could also expand the governance framework proposed in this study by developing reusable compliance toolkits for AI-driven mental health sys-

tems. These toolkits could include standardized documentation templates, ethical review processes, and AI risk assessment procedures tailored to mental health technologies in South Asian contexts.

Finally, technological improvements could focus on supporting offline or low-connectivity deployment scenarios. Edge computing and lightweight AI models could allow screening functionality to operate in regions with limited internet connectivity, thereby extending the reach of the system to rural communities that currently face the greatest barriers to mental health services.

Together, these future research directions highlight the potential for continued development of culturally adaptive digital mental health technologies that are both technically robust and socially responsible.

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