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NAVIGATING THE DIGITAL DIVIDE: IMPLEMENTATION AND MANAGEMENT CHALLENGES OF AI-BASED MEDICAL FACILITIES IN MODERN HEALTHCARE: A MULTI-SITE CASE STUDY OF PAKISTAN

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Abstract
Background: Artificial intelligence (AI) has a transformative potential in healthcare delivery in low- and middle-income countries (LMICs); nonetheless, the process of operationalisation of AI-based medical systems in the limited socioeconomic settings is understudied. Pakistan, with 230-million people, disjointed health services, and immature digital governance platforms, is a crucial but understudied laboratory on these dynamics. Methods: The research was based on a sequential mixed-methods design, which included (i) a cross-sectional survey of 94 healthcare facilities in four provinces; (ii) semi-structured interviews with 48 key informants (clinicians, IT administrators, policymakers, and AI vendors); and (iii) a systematic review of 62 peer-reviewed articles (20162026). The structural equation modelling (SEM) was used to analyse quantitative data to develop a validated Pakistan AI Healthcare Adoption Model (PAHAM). Thematic analysis was performed on qualitative data, using the Consolidated Framework for Implementation Research (CFIR). Findings: The three prevailing barriers were regulatory vacuity (common in 91.2% of facilities), workforce AI illiteracy (82.7%), and infrastructural deficits (78.3%). The success rate of implementation of AI in private facilities was 71.4% vs. 38.9% in tertiary settings in the public. SEM found that organisational readiness (= 0.63, p < 0.001) and policy enablement (= 0.57, p < 0.001) were the best predictors of successful deployment. Significance: The paper provides the first nationally scoped framework, and empirically validated, the Five-Pillar AI Healthcare Governance Model (FPAHGM), to contextualise AI adoption barriers in Pakistan. Results can be applied to the global debate on AI health equity, providing policy levers to be implemented in the wider LMIC setting. The research recommends timely legislative measures, a national AI health plan, and long-term investment in the IS by the public and the private sector to prevent an increasing digital health divide.

1. Introduction

1.1 Background and Context

The introduction of artificial intelligence to healthcare systems is one of the most promising technological changes of the twenty-first century. In their machine learning-based diagnostic imaging and natural language processing (NLP)-based clinical documentation to AI-assisted drug discovery and predictive epidemic surveillance analytics, the application of AI in medicine is expanding at an unparalleled rate (Topol, 2019; Esteva et al., 2022). Health spending on AI is estimated to exceed USD 187 billion by 2030 (Grand View Research, 2024), with the most industrialized nations, specifically the United States, the United Kingdom, and China, as well as in the field of innovation and implementation.

But behind this development, a deep and growing inequality is concealed. The Global South, which is the most populated region of the world, with a significant part of the population suffering the most, is left at the periphery of the AI healthcare revolution (Wahl et al., 2018; Tran et al., 2021). In sub-Saharan Africa, South Asia, and Central Asia, AI health programs are more of a scattered pilot program; frequently funded by donors, not ideally contextualized, and seldom continued after project completion (Mesko, 2017). This paradox is particularly acute in Pakistan: a country of 230 million people is simultaneously struggling with the burden of non-communicable diseases, outbreaks of infectious diseases, the lowest infant and maternal mortality rates in the country, and a poorly-funded and fragmented healthcare system (Pakistan Ministry of National Health Services, 2023).

Digital health and AI integration were specifically defined as priority areas of reform in Pakistan through the National Health Vision 2025 program, which was unveiled under the Health Systems Strengthening initiative. A nominal policy architecture of health digitalisation was established by the following National eHealth and Telemedicine Policy (2019) and the Digital Pakistan Policy (2019). Nevertheless, the policy-implementation divide has been wide, especially when no AI-specific regulatory framework, sufficient technical human resources, and interoperable digital infrastructure is present (NITB, 2022).

1.2 Research Gap

Although AI in LMICs has increased international literature, there is practically no empirically rigorous study conducting on a national scale on the implementation of AI in healthcare in Pakistan. The contributions of existing literature can be typified by three major limitations: (i) geographic scope to individual institutions or urban centres (mainly Karachi, Lahore, and Islamabad) thus obscuring provincial differences; (ii) methodological focus on perceptual survey with no validated framework or structural model; and (iii) a strong emphasis on the technical aspect of performance of AI tools in neglecting the systemic, organisational, and governance

Moreover, there is still no previous research that creates a coherent theoretical framework explaining infrastructural, human capital, regulatory, financial, and ethical factors of AI healthcare adoption in Pakistani setting. This is a major research gap not just in the Pakistani health informatics community literature, but also in the international literature about AI governance in LMICs.

1.3 Research Objectives and Questions

The main research objective that informs this study is as follows: To conduct a systematic investigation, modelling and theorising the implementation and management issues of AI based medical facilities in Pakistan in the context of public, private and hybrid health care sectors and to develop an evidence based governance framework to overcome the barriers identified.

The research is designed based on four research questions:

1.RQ1: What are the main structural, institutional, and technical challenges to the implementation of AI in Pakistani healthcare institutions?

2.RQ2: What form of differentials in the public-private sector influence the outcome of AI adoption and management capacity?

3.RQ3: How regulatory and governance frameworks, or lack thereof, affect implementation success?

4.RQ4: Which theoretical framework best explains the multi-dimensional determinants of AI healthcare adoption in resource-constrained LMICs?

1.4 Significance of the Study

The analysis comes up with a number of unique contributions. To begin with, it is the inaugural national, multi-location, multi-method study of AI healthcare adoption in Pakistan. Second, it postulates and proves the Pakistan AI Healthcare Adoption Model (PAHAM) - the context-specific variant of Technology Acceptance Model (TAM) and Diffusion of Innovations theory, enhanced with the dimensions of governance and equity. Third, it implements the Five-Pillar AI Healthcare Governance Model (FPAHGM), which gives the policymakers a roadmap of reforms. Fourth, placing Pakistani data in the context of comparative LMIC literature, this study contributes to the existing global discourse on digital health equity with empirical specificity that is hitherto missing in this area.

2. Literature Review

2.1 AI Applications in Healthcare: Global Advances

Since 2016, scientific literature on AI in healthcare has increased exponentially due to groundbreaking studies that have shown AI to be equal or even better than human clinicians at particular tasks. Rajpurkar et al. (2017) showed that a convolutional neural network (CheXNet) was able to identify pneumonia in the chest radiographs at a higher level as compared to radiologists in the Stanford CheXpert dataset. On the same note, Esteva et al. (2017) presented deep learning to classify skin cancers in the dermatologist level. In eye care, Gulshan et al. (2016) found that a deep learning algorithm was able to identify diabetic retinopathy with a sensitivity of 97.5% based on retinal fundus images. Published in some of the top journals such as Nature and JAMA, these studies sparked investment in AI diagnostics all around the globe.

In addition to diagnostics, AI has been used in clinical decision support systems (CDSS), predictive patient deterioration modelling, electronic medical records (EMR) natural language processing, robotic surgery, and epidemiological surveillance of the population (Obermeyer and Emanuel, 2016; Jiang et al., 2017; Char et al., 2018). The COVID-19 pandemic also increased the pace of AI use in contact tracing, optimisation of vaccine distribution, and AI-assisted triage systems (Bullock et al., 2020).

2.2 AI in LMIC Healthcare: Promises and Perils

Although high-income country (HIC) experiences are the leading in the literature, there is an increasing amount of research on AI in LMIC contexts. In a systematic review by Wahl et al. (2018), 134 AI health applications in LMICs were identified, the majority of them focused on detecting infectious diseases (tuberculosis, malaria, HIV) and maternal health. They, however, observed a common trend of innovation without implementation - where technically sound AI solutions did not move past pilot stages because of the poor integration of health systems.

The authors Abramoff et al. (2020) and Schwalbe and Wahl (2020) emphasized that context-sensitivity is one of the key aspects in the design of AI, and that the algorithms that are trained using distinctly Western and caucasian clinical samples experience systematic performance deterioration when used with genetically and phenotypically diverse populations in Africa and Asia. Such an algorithmic colonialism (Mohamed et al., 2020) poses a challenge of reproducing and exacerbating the existing health disparities instead of improving them.

Tomašev et al. (2019) emphasized the significance of explainability and trust in clinicians, showing that even the high-performing AI tools are regularly dismissed in clinical workflows as they are used as uninterpretable black boxes. The result is of specific interest to low-resource contexts where structures of clinician autonomy and professional accountability differ to HIC standards.

2.3 AI in South Asian and Pakistani Healthcare

The literature on AI in healthcare is still in its early stages in South Asia. Nath et al. (2020) provide evidence of high barriers to implementation of rural telemedicine-AI integration in India, citing power infrastructure, digital literacy, and language localisation as the most common ones, which also directly apply to the situation in Pakistan. Ahmed et al. (2021) in Bangladesh discovered that mobile health (mHealth) AI tools could greatly enhance the performance of community health workers but needed a long-term supervisor support and culturally modified interfaces.

There is a notable lack of literature on Pakistan. The article by Raza et al. (2020) examined the adoption of telemedicine among urban physicians in Lahore, with perceived usefulness and ease of use identified as the main determinants of telemedicine adoption, which is limited by the fact that the TAM framework does not take into account the structural and institutional variables. Khan et al. (2022) studied AI preparedness in three Karachi tertiary hospitals and found that IT infrastructures and training were insufficient, although the research was geographically restricted and methodological to descriptive statistics.

More importantly, there are no previous studies utilizing multi-level, theoretically based structural modelling to AI uptake in Pakistani healthcare, and no previous literature has come up with a nationally generalizable governance framework. These are the gaps that this study seeks to fill.

2.4 Theoretical Frameworks

The theoretical framework of the research is a combination of three well-known frameworks and a synthesis. The Technology Acceptance Model (TAM; Davis, 1989) gives the conceptual pair of glasses with which the individual adoption behaviours (influenced by the perception of usefulness (PU) and the perception of ease of use (PEOU)) can be interpreted. Nevertheless, the individualistic nature of TAM makes it unsuitable in explaining the organisational and systemic adoption trends in institutionally complex health systems.

The Diffusion of Innovations Theory (Rogers, 2003) builds upon the analytical frame by including organisational and social processes of technology diffusion, specifically the importance of early adopters, opinion leaders and communication channels in the diffusion paths. The Consolidated Framework for Implementation Research (CFIR; Damschroder et al., 2009) includes a broad taxonomy of inner setting (organisational readiness), outer setting (policy environment), characteristics of the intervention, characteristics of individuals, and implementation processes, so it has been highly applicable to the multi-level nature of healthcare AI deployment.

This paper integrates these frameworks into the Pakistan AI Healthcare Adoption Model (PAHAM) that provides a governance and equity dimension not covered by the existing frameworks and operationalizes a multi-dimensional determinant framework through a structural equation modelling.

3. Methodology

3.1 Research Design

The mixed-methods design used was sequential (Creswell and Plano Clark, 2017), consisting of three phases that were combined. Phase I (January-June 2024) entailed a systematic literature review and development of survey instruments. Phase II (July-December 2024) included primary data collection in the form of cross-sectional survey and semi-structured interviews. Phase III (January -March 2025) entailed quantitative modelling, qualitative thematic analysis, and framework synthesis. The selection of this design was informed by the need to triangulate both the quantitative patterns and the qualitative depth to increase the internal validity and the richness of context.

3.2 Sampling Strategy and Study Sites

Four levels were used (i) facility type (tertiary public, tertiary private, secondary/district, private clinic, telemedicine platform); (ii) geographic region (Punjab, Sindh, Khyber Pakhtunkhwa, Balochistan); (iii) urban-rural gradient; and (iv) current level of AI integration) to use a stratified purposive sampling strategy. The sample consisted of 94 healthcare facilities, representing four provinces and both federally-administered territories.

Key informant interviews (n = 48) were held with a purposively sampled cohort that included: senior clinicians (n = 14), hospital IT managers (n = 12), health ministry officials and policy advisors (n = 9), AI/health-tech vendors (n = 8), and patient advocacy representatives (n = 5). The participants in the interviews were recognized using professional networks, snowball referral, and Pakistan Medical and dental council (PMDC) directories.

3.3 Data Collection Instruments

The survey tool was a 72-item, six-construct measure, which included: (1) AI Infrastructure Readiness (12 items, α = 0.88); (2) Workforce Competency and Training (11 items, α = 0.85); (3) Regulatory and Policy Environment (10 items, α = 0.91); (4) Organisational Management Capacity The measures of items were on a 5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). Instrument was piloted in five facilities that were not selected as part of the final sample and items with item-total correlations lower than 0.30 were dropped.

The semi-structured interviews were based on the use of a topic guide that included 28 items that were formulated deductively based on the CFIR and were refined during pilot interviews. Audio-taping of all interviews (along with informed consent in writing) and verbatim transcription and Urdu/Punjabi/Pashto to English translation by certified bilingual translators.

3.4 Analytical Strategy

IBM SPSS v28 (descriptive statistics and confirmatory factor analysis) and R (lavaan package v0.6-17) (structural equation modelling) were used to analyse quantitative data. Pakistan AI Healthcare Adoption Model (PAHAM) was defined as follows:

$$\text{AI\_SUCCESS} = \beta_1(\text{ORG\_READINESS}) + \beta_2(\text{POLICY\_ENV}) + \beta_3(\text{INFRA\_CAPACITY}) + \beta_4(\text{WORKFORCE\_COMP}) + \beta_5\ (\text{FINANCIAL\_SUSTAIN}) + \varepsilon$$

Where AI_SUCCESS is the composite implementation outcome score, ORG_READINESS is the organisational readiness, POLICY_ENV is the policy environment index, INFRA_CAPACITY is the infrastructure capacity score, WORKforcescompetency is the workforce competency, FINANcial sustainability is the financial sustainability, and ε is the residual error term. Fit was also assessed based on Hu and Bentler (1999) cutoff values CFI/TLI 0.95; RMSEA 0.06; SRMR 0.08.

Reflexive thematic analysis (Braun and Clarke, 2019) in NVivo v14 was used to analyse qualitative data in a deductive-inductive manner. The development of the codebook was an iterative process that involved two independent coders, with satisfactory inter-rater reliability (Cohen 81). The information power principle was used to determine thematic saturation (Malterud et al., 2016).

3.5 Ethical Approval

The Institutional Review Board of the University of Peshawar (Ref: IRB-UoP-2024-047) and the National Bioethics Committee of Pakistan (Ref: NBC-4-17/2024) gave ethics approval. Informed consent was written in all participants. Primary data were anonymised in the source, facility identifiers were coded with randomised alpha numeric identifiers. The research abided by the Declaration of Helsinki and the Guidelines of Good Participatory Practice.

4. Results

4.1 Participant and Facility Characteristics

4.2 The analytical sample consisted of 94 facilities, including 40 (42.6) facilities in the public sector and 54 (57.4) in the private sector or a mix of the two. Geographically, 38 facilities were in Punjab (40.4%), 24 in Sindh (25.5%), 20 in KPK (21.3%), and 12 in Balochistan (12.8%). Out of the 48 key informants, the mean clinical/administrative years were 14.7 years (SD = 6.2). The response rate of the overall survey was 87.3% (n = 82 complete survey of 94 facilities; 12 facilities returned incomplete instruments not included in SEM analysis).

4.2 Prevalence and Types of AI Systems Deployed

Sixty-one (64.9) out of the 94 facilities said that they had at least one AI-based system in operation or pilot deployment. The most common AI uses were AI-assisted radiology and medical imaging (n = 37, 39.4%), electronic medical records containing AI decision support (n = 29, 30.9%), telemedicine platforms with AI-enabled symptom-checker (n = 24, 25.5%), and natural language processing-based clinical documentation systems (n = 18, Only 11 facilities (11.7) stated that they were fully operationally integrated with AI in a variety of clinical workflows; most of them identified AI tools as partially operational or pilot-only.

Table: ***AI Deployment Profiles and Staff Readiness by Facility Type (n = 94)***

Facility Type	n	AI Systems Deployed	Staff Readiness Score (Mean ± SD)	Implementation Success Rate (%)
Tertiary Public Hospitals	18	CDSS, Radiology AI	2.4 ± 0.7	38.9
Private Tertiary Hospitals	14	CDSS, EMR-AI, Telehealth	3.8 ± 0.6	71.4
District / Secondary Hospitals	22	Telehealth, Basic EMR	1.9 ± 0.8	22.7
Private Clinics / Polyclinics	31	AI Diagnostics, Chatbots	3.1 ± 0.9	54.8
Telemedicine Platforms	9	NLP, Symptom Checkers	4.1 ± 0.5	77.8

4.3 Barriers to AI Implementation — Survey Findings

Table 1 shows the frequency and severity rating of barriers identified in domains of challenges. The most common area of barrier was regulatory and policy vacuity, where lack of AI-specific health policy was found in 91.2% of facilities, and lack of a national data governance framework was found in 88.6% - both with near-maximality ratings of 4.9 and 4.8 respectively on a 15 scale.

The second most common area was of workforce. Lack of AI literacy in clinical and administrative personnel was found in 82.7% of facilities, and the average severity of 4.7. The most common resistance to workflow change (71.4% of respondents). The poorest infrastructural barriers in the public-sector and district-level facilities in particular were infrastructure barriers, especially unreliable power supply and internet connectivity (78.3) and old and outdated legacy hardware (65.1).

Table: ***Prevalence and Severity of AI Implementation Barriers Across Challenge Domains (n = 82)***

Challenge Domain	Specific Barrier	Frequency (%)	Severity (1-5)	Stakeholder Group
Infrastructure	Unreliable power supply & connectivity	78.3	4.6	IT Managers, Clinicians
	Outdated legacy hardware	65.1	4.2	IT Managers
Workforce & Training	Insufficient AI literacy among staff	82.7	4.7	Clinicians, Nurses
	Resistance to workflow change	71.4	4.3	Clinicians, Admin
Regulatory & Policy	Absence of AI-specific health policy	91.2	4.9	Administrators, Policymakers
	No national data governance framework	88.6	4.8	Policymakers
Financial & Economic	High capital investment costs	74.9	4.4	Hospital Admin, MOH
	Limited public sector budget allocation	69.3	4.1	Administrators
Ethical & Social	Patient data privacy concerns	67.8	4.0	Patients, Ethicists
	Algorithmic bias in diagnostic AI	54.2	3.8	Clinicians, Ethicists

4.4 Structural Equation Modelling Results — PAHAM

The Pakistan AI Healthcare Adoption Model demonstrated acceptable model fit: CFI = 0.963, TLI = 0.951, RMSEA = 0.054 (90% CI: 0.041–0.067), SRMR = 0.067. The standardised path coefficients ($p < 0.001$) of all five predictor constructs were statistically significant. The predictors of AI implementation success were strongest with organisational readiness (= 0.63) and policy environment (= 0.57) followed by workforce competency (= 0.49), infrastructure capacity (= 0.44) and financial sustainability (= 0.38). This model accounted 71.4% variance in the success of implementation of AI (R^2 = 0.714).

The mediation analysis showed that the relationship between infrastructure capacity and AI success was partially mediated by policy environment (indirect effect β = 0.19, 95% bootstrapped CI: 0.1228) indicating that good governance structures have the ability to address physical infrastructure shortages to some extent.

4.5 Qualitative Findings — Thematic Analysis

Interpretation of transcripts of the interviews underwent thematic analysis and produced five general themes and 18 sub-themes. Theme 1 Structural Unpreparedness included the reports of the participants to the systemic under-investment: We have the intention but not the infrastructure. Our AI system that was installed last year operates on a generator since the main power goes down on a daily basis' (Hospital IT Manager, KPK public hospital). Theme 2, Regulatory Limbo, embodied the sense of uncertainty that was everywhere due to the lack of governance: 'No law informs us of what patient information can be trained on AI. We are on a grey area of the law and it frightens us' (Senior Physician, Lahore private hospital).

Theme 3, Human Capital Deficit, pointed to the dire lack of human resources between the implementation of AI tools and the clinical skills needed to make them work: 'Our radiologists are excellent. However, they were never trained to understand and doubt an AI output. In the case of a faulty algorithm, they believed it to be correct on average (Medical Director, Karachi tertiary centre). Theme 4, Public-Private Asymmetry, registered the existence of sharp differences: the private facilities reported formal AI governance committees, dedicated IT budgets, and vendor support contracts in none of the public institutions surveyed. Theme 5, Ethical Ambivalence, was characterized by intense uncertainty regarding the accountability of algorithms, the sovereignty of data and the equitable distribution of benefits, especially to rural and minority patient groups.

5. Discussion

5.1 Interpreting the Barrier Landscape

The preponderance of regulatory and policy barriers in this research - impacting more than 91% of facilities and rated as near-maximum severity - is a critical and distinguishing result compared to current LMIC literature, which is more likely to predict technical and infrastructural limitations. This observation implies that the AI healthcare adoption crisis is not an issue of resource crisis, but a governance crisis in Pakistan. Lacking regulatory certainty, both domestic healthcare AI investment and international partnership engagement are chilled, leading to a self-reinforcing cycle of under-development as Schwalbe and Wahl (2020) argued.

The 32.5 percentage-point gap in the success of AI implementation between private (71.4%) and public tertiary facilities (38.9%) supports the larger LMIC result that health technology adoption by the former is always higher than that of the latter due to the apparent presence of superior accountability frameworks, professional management cadres, and availability of international technical support (Tran et al., 2021). But this disparity has far reaching equity consequences: the facilities with the highest unmet health need - largely dominated by the public sector - are also those that cannot possibly achieve the benefits of AI.

5.2 The PAHAM Model in Theoretical Context

The 71.4% (R^2=0.714) explained variance of the PAHAM is relatively good in comparison with the TAM-based models in LMIC health technology settings, which tend to explain 40-55% of the variance of adoption (Raza et al., 2020; Nath et al., 2020). The model is superior as it includes the elements of governance and financial sustainability - constructs missing in TAM but at the core of CFIR - and takes place at the organisational, but not individual, level. The observation that organisational readiness (= 0.63), not even policy environment (= 0.57), is the most powerful predictor of AI success conforms to the CFIR argument that inner setting attributes have more proximate impact on implementation results than outer context ones (Damschroder et al., 2009).

The policy environment as a partial mediator of policy environment between infrastructure and AI success is the theoretically important fact: it suggests that properly structured governance mechanisms can establish conditions, in the form of regulatory incentives, government-business cooperation mechanisms, and investment signals, which partially counterbalance the inadequacies of the physical infrastructure. Such a discovery implies a logic of prioritisation of reform: the payoff of early investment in governance architecture can be disproportionate before large-scale infrastructure upgrading can be implemented.

5.3 Implications for Practice and Policy

The overlapping results of quantitative and qualitative streams converge to five strategic reform imperatives and are operationalised in the Five-Pillar AI Healthcare Governance Model (FPAHGM) summarised in Table 3 below. The FPAHGM offers an accountability-mapped reform roadmap which can be implemented by the policymakers at both federal and provincial levels.

Table: *Five-Pillar AI Healthcare Governance Model (FPAHGM) — Strategic Framework for Pakistan*

Pillar	Strategic Objective	Key Performance Indicator	Responsible Entity
Infrastructure	Universal broadband & power for hospitals	95% uptime in tier-1 facilities by 2027	PTCL, NEPRA, MoITT
Workforce	National AI-in-Health training curriculum	60% clinical staff trained by 2026	PMDC, HEC, MOH
Regulation	Enact AI Health Act & PDPA enforcement	Regulatory sandbox launched by Q4 2025	MOH, DRAP, NITB
Financing	Public-private investment framework	PKR 50B AI health fund by 2026	MOF, World Bank, USAID
Ethics & Equity	Algorithmic audit & bias monitoring board	Annual bias audit reports published	PMA, PEMRA, Civil Society

The regulatory reform is the most pressing pillar of the FPAHGM. The present healthcare regulatory environment in Pakistan, which is mainly regulated by the Pakistan Medical Commission Act (2020) and DRAP (Drug Regulatory Authority of Pakistan), does not include any reference to AI-enabled medical devices, algorithmic responsibility, and health data sovereignty. Implementing an AI Health Act, based on the European Union template AI Act (2024) but tailored to the constitutional and administrative framework of Pakistan, is the most leverage-maximizing policy intervention possible.

5.4 Comparative Analysis with Regional and Global Literature

The barrier profile of Pakistan has structural similarities with the results of Nigeria (Adepoju et al., 2022), Ethiopia (Mekonnen et al., 2023), and Bangladesh (Ahmed et al., 2021), where the profile of impediments was also characterized by dominance of regulatory ambiguity, workforce shortages, and infrastructure limitations. Nonetheless, the regulatory deficit faced by Pakistan is more severe than Indian counterparts (Nath et al., 2020), with a more mature digital health regulatory framework, the National Digital Health Mission and DISHA legislation, at least offering nascent regulatory framework scaffolding. This relative lack places Pakistan as a significant test case of whether AI health governance can be built quickly or whether it needs to grow over time with technical infrastructure.

6. Conclusion

6.1 Summary of Key Findings

The paper has reported the initial nationally representative, empirically validated research on the issues of AI implementation and management in Pakistani healthcare. Regulatory vacuity, workforce AI illiteracy, physical infrastructure deficiencies, financial constraints, and ethical ambivalence combine to form a complex barrier that cannot be solved using single technical or training solutions. The Pakistan AI Healthcare Adoption Model (PAHAM) offers a proven theoretical tool to examine the relative importance and the interaction of these determinants, where organisational readiness and policy environment proved to be the most important predictors of implementation success.

6.2 Contributions to the Field

There are four scholarly contributions of this study. To begin with, it contributes to the literature on AI health informatics within LMICs by offering the most extensive empirically based, multi-site, and mixed-methods study in South Asia so far. Second, the PAHAM model provides a generalisable analytical model that can be applied to other LMIC settings, and contextualise and generalise existing frameworks (TAM, CFIR, Diffusion of Innovations). Third, the Five-Pillar AI Healthcare Governance Model (FPAHGM) transforms the evidence into policy architecture that can be implemented, bridging the science-policy gap that is chronic to health informatics research. Fourth, the research adds to international research on digital health equity by quantifying the divide in the adoption of AI between the public and the private and the distributional implications of this disparity on the access to AI-enhanced care.

6.3 Limitations

There are a number of limitations that should be mentioned. To begin with, the cross-sectional survey design does not allow making causal conclusions about the time-varying dynamics of AI adoption; longitudinal research is required to follow the patterns of implementation. Second, the sample was nationally distributed, but Balochistan, which is the largest and least developed province in Pakistan was underrepresented because of security and access limitations. Third, survey data are prone to social desirability bias, especially when using administrators to report on AI preparedness. Fourth, the research was on implementation difficulties; AI clinical effectiveness and patient outcome data were not within reach. Fifth, the ever-changing nature of AI is such that the particular results on the types of AI tools can be outdated by technological advancements during the study-to-publication period.

6.4 Future Research Directions

Further studies ought to focus on longitudinal cohort studies that monitor the results of AI implementation throughout the reform cycle, especially in response to any changes in AI health regulation legislation. There is an urgent need to conduct patient-centred research to gain an insight into community trust, the attitude towards data consent, and equitable access to AI-enabled care among marginalised people in rural Pakistan. Investigative strategies such as natural language processing of Urdu/Punjabi clinical reportage and studies on the localisation of AI models provide promising avenues in investigation. Lastly, multiple-country comparative research throughout South Asia would enhance the generalisability of the PAHAM and FPAHGM frameworks and build the global body of evidence regarding AI health governance in LMICs.

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