

# Socio-technical Barriers to AI Diagnostic Tool Integration in South Asian Primary Healthcare: A Scoping Review

Om Vaswani<sup>1</sup>, Muhammad Ahmed Abdullah<sup>1</sup>, Viveck Vasvani<sup>1</sup>, Parkash<sup>2</sup>

<sup>1</sup> Health Services Academy HAS, Islamabad

<sup>2</sup> Ziauddin University faculty of Health Science, Sukkur, Pakistan

\* Corresponding author: Om [Vaswani — dr.omvaswani@gmail.com](mailto:dr.omvaswani@gmail.com)

## Abstract

**Background:** Artificial intelligence (AI)-based diagnostic tools and digital decision support systems are increasingly deployed in South Asian primary healthcare (PHC). However, real-world integration is shaped by socio-technical constraints affecting feasibility, safety, acceptance, and continuity of care.

**Objective:** To map published evidence on AI-based diagnostic tools in South Asian PHC settings and synthesize reported socio-technical barriers to their integration.

**Methods:** A scoping review was conducted using PubMed as the sole database. Keyword and MeSH-based search strategies combined AI, PHC, implementation/barrier, and South Asia geography terms. Two reviewers independently screened titles/abstracts and full texts using Rayyan. Data were charted using a standardized form and barriers synthesized thematically into five domains: (1) technical/infrastructure, (2) human factors, (3) ethics/data governance, (4) health system/organizational, and (5) socioeconomic/access.

**Results:** Of 1,759 records screened, 14 evidence sources were included primarily from India (n=11), Bangladesh (n=2), and Pakistan (n=1). AI applications included diabetic retinopathy screening, cervical and breast cancer screening, tuberculosis/chest X-ray computer-aided detection, COVID-19 surveillance, and CDSS/DDSS. Barriers were multi-level: unreliable electricity and connectivity; image quality degradation; prediction instability from WhatsApp-compressed CXRs; workflow burden; ethical risks including inadequate consent and unclear accountability; weak referral pathways with low follow-up adherence (~13–17%); and socioeconomic barriers including transport costs and competing priorities.

**Conclusion:** Integration of AI diagnostic tools in South Asian PHC is constrained by interacting socio-technical barriers. Implementation strategies should address infrastructure readiness, workflow redesign, governance/accountability, and referral completion to translate AI screening into patient benefit.

**Keywords:** Artificial Intelligence, Diagnostic Tools, Implementation, Primary Health Care, South Asia, Socio-technical

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## Article Summary:

### Strengths and limitations of this study

**Strengths:** (1) PubMed-only methodology is good for massive screening; (2) independent dual reviewer screening with exclusive use of Rayyan AI for prioritizing screening; and (3) synthesis of multiple AI modalities, including CAD, Rule-Based AI, CDSS/DDSS and multiple PHC delivery types.

**Limitations:** (1) A search in one database may not be able to retrieve information from other databases; (2) there is heterogeneity in study design / outcome measures; and (3) whilst some studies were published in advance of peer-review, some studies included both a protocol and a pre-print version of the paper.

## 1. Introduction

Primary healthcare (PHC) in South Asia is delivered through diverse models, including public-sector facilities, community-based screening programs, and tele-primary care platforms. Across these models, AI-based diagnostic tools are increasingly used to support screening, triage, and clinical decision-making. Examples include: CDSS integration into India's national NCD platform with task shifting to nurses; [1] household-level CHW programs combining AI-enabled risk assessment and digital referrals in Bangladesh; [2] and an embedded digital decision support system (DDSS) in Pakistan's tele-primary care platform being evaluated for feasibility, acceptability, and perceived quality of care. [3] There are many social barriers preventing the efficient integration, utilization and application of AI tools into everyday life. The factors that influence these applications need further evaluation to provide an understanding of the various types of users and their ways of using AI tools.

The strongest concentration of published evidence within this review concerns DR screening models in India, including facility-based and community-based AI-assisted approaches. [4-6] The evidence base also includes AI tools for cervical cancer screening within nurse-led "screen-and-treat" pathways, where real-world image noise drives misclassification and overtreatment trade-offs; [9] and breast health screening using AI-enabled thermography in underserved urban settings, where stigma, fear, and access barriers shape participation and follow-up. [10] For TB, large-scale CAD validation across primary health centers and a tertiary site has been reported, [11] and adoption evidence indicates that provider intent to use AI for CXR TB

diagnosis varies by state context and trust relationships particularly among informal and AYUSH providers who often serve as first contact.[12] Technical evidence further suggests that smartphone-mediated workflows common in low-bandwidth settings (eg, WhatsApp transmission) can compress CXR images and destabilize AI predictions and explainability creating a deployment-specific technical risk.[13] Bangladesh's national COVID-19 surveillance platform illustrates rule-based AI screening at scale with offline sync and centralized dashboards, while also documenting integration limitations.[14]

Although this body of evidence spans multiple conditions and tool types, barriers to integration are dispersed and described inconsistently. A scoping review is appropriate to map the scope of available evidence and synthesize socio-technical barriers shaping integration into South Asian PHC.

## Objectives

1. To map the published evidence on AI-based diagnostic tools used in PHC or first-contact care settings in South Asia.
2. To synthesize reported socio-technical barriers to integration, grouped into technical/infrastructure, human factors, ethics/data governance, health system/organizational, and socioeconomic/access domains.

## Methods

### Search strategy

PubMed was used as the sole database due to the high volume of potentially eligible records. The search included two strategies (Appendix 1): (1) a keyword strategy and (2) a MeSH-enhanced strategy. Limits were applied for English language and publication years 2021-2026.

### Eligibility criteria (PCC)

**Population:** healthcare providers (eg, doctors, nurses, CHWs/LHWs), patients, or health-system stakeholders.

**Concept:** AI-based diagnostic tools, screening/triage systems, and decision support tools used for diagnosis or diagnostic pathway decisions. Tools used solely for administrative scheduling or non-diagnostic functions were excluded.

**Context:** PHC settings, basic health units (BHUs), community screening programs, rural clinics, and tele-primary care platforms in South Asia. Studies conducted exclusively in tertiary settings without PHC linkage were excluded.

**Geography:** South Asian countries (search included Pakistan, India, Bangladesh, Nepal, Sri Lanka; included evidence ultimately came from India, Pakistan, Bangladesh).

**Study type:** original research (quantitative, qualitative, mixed-methods), system/implementation reports, and protocols when they described PHC integration context. Editorials and conference abstracts without full text were excluded.

**Time/language:** English; 2021-2026.

### Study selection process

Screening was performed in Rayyan.

- Screening began 16 Jan 2026.
- Full-text screening began 01 Feb 2026.

Two reviewers independently screened titles/abstracts and full texts. Rayyan AI

prioritization was used only to support screening order; inclusion decisions were based on reviewer assessment. Disagreements were resolved through discussion.

### Data charting

A standardized data charting form was used to extract:

- bibliographic details (year, country)
- PHC context (facility/community/tele-PHC)
- AI tool type (DL/ML image tool; CAD; rule-based AI; CDSS/DDSS)
- clinical domain (DR, cervical cancer, breast health, TB/CXR, COVID-19, NCD risk)
- integration outcomes (eg, refusal, usability/acceptability, referral adherence)
- reported barriers and mitigation/adaptation strategies

### Synthesis of results

We used descriptive analysis to summarize the included evidence. We synthesized barriers thematically into five socio-technical domains:

1. technical/infrastructure; 2) human factors; 3) ethics/data governance; 4) health system/organizational; 5) socioeconomic/access.

### Critical appraisal

Critical appraisal was not performed because the purpose of this scoping review was to map evidence and integration barriers, not to estimate intervention effects.

### Results

#### Study selection

The PubMed search returned **1,759** records. After removing **9** duplicates, **1,750** records underwent title/abstract screening. **1,678** were excluded and **72** full texts were assessed. After full-text screening, 58 were excluded; reasons are summarized in **(Table 1)**. **14** evidence sources were included.

**Figure 1** PRISMA flow diagram showing study selection process.

| <b>Table 1</b> Reasons for exclusion of full-text reports (n = 58) |          |
|--------------------------------------------------------------------|----------|
| <b>Reason for exclusion at full-text stage</b>                     | <b>n</b> |
| Not primary healthcare/first-contact care setting                  | 14       |
| Not conducted in South Asia or no South Asia-specific data         | 11       |
| Not an AI-based diagnostic or clinical decision-support tool       | 16       |
| No data on implementation or integration barriers                  | 9        |

|                                                                                      |           |
|--------------------------------------------------------------------------------------|-----------|
| Not eligible evidence type (e.g., review, editorial/commentary, conference abstract) | 6         |
| Full text not available                                                              | 0         |
| Other reasons (e.g., wrong outcome focus, insufficient methodological detail)        | 2         |
| <b>Total</b>                                                                         | <b>58</b> |

### Characteristics of included evidence (n=14)

Characteristics of all 14 included evidence sources are presented in **(Table 2)**.

Included evidence sources represented India (n=11), Bangladesh (n=2), and Pakistan (n=1) **(Table 2)**.

Domains included:

- **DR screening in PHC/community:** reach, implementation, adoption, and referral adherence; and real-world validation/integration of DR AI systems.[4-6]
- **Retinal image quality/gradability:** DL model to classify gradability for handheld non-mydriatic images used in community screening.[7]
- **Trustworthy AI governance for DR:** qualitative stakeholder perspectives on transparency, consent, privacy, and accountability.[8]
- **Cervical cancer screening:** VIA-AI tool in nurse-led screen-and-treat workflow; misinterpretation driven by image artifacts and clinical mimics.[9]
- **Breast health screening:** AI thermography in urban slums; stigma/fear and follow-up barriers.[10]
- **TB/CXR:** CAD validation across PHCs and one tertiary center; and provider intent to adopt AI CXR TB diagnostics among informal/AYUSH providers.[11,12]
- **COVID-19:** national rule-based AI surveillance in Bangladesh; and WhatsApp compression effects on CXR AI prediction reliability and explainability.[13,14]
- **Decision support:** India national NCD CDSS integration with task shifting; Bangladesh CHW AI/CDSS model; Pakistan tele-PHC DDSS protocol.[1-3]

**Table 2** Characteristics of included evidence sources (n=14)

| Ref | Country             | PHC context                   | Tool type                        | Domain                |
|-----|---------------------|-------------------------------|----------------------------------|-----------------------|
| 1   | India               | PHC/CHC/DH public system      | Algorithmic CDSS + task shifting | HTN/DM care           |
| 2   | Bangladesh          | Household/CHW model           | AI/CDSS + digital referrals      | NCD screening/risk    |
| 3   | Pakistan            | Tele-PHC e-clinics            | ML-based DDSS (protocol)         | Febrile illness       |
| 4   | India               | HWC + home/community          | Offline AI + human screening     | DR                    |
| 5   | India               | HWC + home/community          | Offline AI + human screening     | DR                    |
| 6   | India               | PHC/CHC                       | AI validation + integration      | DR                    |
| 7   | India               | Community screening dataset   | DL gradability                   | Retinal image quality |
| 8   | India               | Stakeholders                  | Qualitative governance           | DR ethics/governance  |
| 9   | India               | Nurse-led clinics             | DL VIA-AI                        | Cervical cancer       |
| 10  | India               | Urban slums/UHTC-linked       | AI thermography                  | Breast health         |
| 11  | India               | 12 PHCs + 1 tertiary          | CAD                              | TB/CXR                |
| 12  | India               | Informal/AYUSH                | Adoption intent                  | TB/CXR AI             |
| 13  | India/LMIC-relevant | Smartphone/messaging workflow | DL robustness                    | COVID/CXR             |
| 14  | Bangladesh          | National/community            | Rule-based AI                    | COVID-19              |

## Thematic synthesis: socio-technical barriers to AI integration

### 1) Technical and infrastructure barriers

There were significant issues with both power supply stability and hardware reliability during the deployment of PHCs.

The implementation of DR (Digital Radiology) screening was greatly affected by power outages and fluctuations in voltage that affected equipment reliability and the ability to maintain a workflow and create solutions through stabilizers, generators, and troubleshooting.[4] Limiting factors like connectivity and reliance on the internet affected the ability to implement decision support. For example, there were many attempts in the national CDSS (Clinical Decision Support System) integration effort in India to explore offline options, but these were ultimately rejected due to security issues and the complexity of operating a local server; essentially, this would require daily maintenance.[1] In Bangladesh, this was reflected in the need for offline programs, technical issues associated with server operation, and poor/downstream data linkages for referral purposes.[2,14]

Conditions of image capture and image quality were cited repeatedly as restrictions on the effectiveness of screening in both digital and traditional hardware. For example, in order for DR screening in facilities to produce good quality images (gradable) controlled, low light conditions analyzed and a dark room could assist with improving gradeability and reducing the amount of retakes.[4,6] There was research to determine retina gradeability with retinal handheld imaging; non-mydriatic retinal handheld imaging had high technical failure rates and immediate re-capture of images could be predicted based on the information received from on-device gradeability assessments.[7] In VIA-AI cervical cancer screening, there was consistent presence of image "noise" and capture artifact (i.e., glare from flash, mucus, blood on the image, low quality) that led to incorrect results from the AI (artificial intelligence) system.[9].

The compression used when transmitting images from a smartphone will be an impediment to the implementation of CXRs (chest X-ray). The compression of a CXR (chest X-ray) image sent using WhatsApp resulted in "prediction instability" and reduced explainability (out of picture) continued to add a degree of uncertainty to the result of the decision level AI in the CXRs and

may also affect the way in which the AI behaves to make AI decisions at the level of messaging.[13]

## **2) Human factors: acceptability, trust, training, stigma, and workflow burden**

**Belief intent gaps** were evident. Among informal and AYUSH providers, belief in AI benefits for TB diagnosis was high but willingness to try AI was lower and varied by state context and trust in radiologists.[12]

**Workflow burden and clinician time constraints** were major barriers for CDSS integration in public PHC. Low physician acceptance and limited time prompted task shifting to nurses and the use of printouts when digital interaction was constrained.[1]

**Training needs and learning curves** were important in screening. DR programs reported structured training for optometrists and improvements in performance over time.[4,6]

**Fear, stigma, and asymptomatic perception** reduced participation and follow-up. Breast screening work identified stigma/fear and low awareness, with substantial loss to follow-up particularly among asymptomatic women.[10] Similar perceptions (eg, “good eye health”) reduced DR screening participation.[4,5]

## **3) Ethics and data governance barriers**

Qualitative stakeholder evidence identified ethical barriers to trustworthy AI integration in DR screening, including lack of transparency in data collection, inadequate consent, low privacy literacy, re-identification risks, and unclear accountability/liability.[8] These issues were discussed as reinforcing “data colonialism” risks in LMIC settings.

## **4) Health-system and organizational barriers**

**Weak referral pathways and low follow-up adherence** were consistent across screening programs. DR adoption/implementation studies reported low referral adherence after screening (commonly ~13-17%), even when counseling and immediate results were provided.[5,6] Barriers included transport constraints, work/seasonal demands, family dependence, and competing priorities.[4-6] Breast screening similarly documented loss to follow-up driven by asymptomatic status and economic barriers.[10]

**Interoperability limitations** were described in digital systems, including incomplete integration with hospital systems and challenges in outcome tracking and referral data linkage.[2,14] CDSS integration into national platforms required extensive stakeholder coordination and system redesign.[1]

## **5) Socioeconomic and Access Barriers**

Lack of access to transportation, long distance (or in some cases, lack of access at all), problems with mobility, loss of earnings, and low health literacy were all contributing factors for non-compliance and/or refusal to seek diabetic retinopathy and breast cancer screening.[4,5,10] In Bangladesh, low willingness to pay for access to glucose monitoring was also one of the factors that decreased uptake and made it difficult to interpret longitudinal outcomes.[2]

## **Discussion**

This scoping review analyzed existing literature regarding AI-based diagnostic devices for use in South Asian primary healthcare and also identified the existence of multiple socio-technical barriers to adoption (common to all types of devices) across clinical domains.

Infrastructure and context of use govern the feasibility and safety of a device. The implementation and performance of devices have been adversely affected by power instability, dependence on the internet, and environmental limitations.[1,4,14] In particular, imaging-based AIs have been impacted by capture conditions and real-world artifacts[7,9]. Smartphone-

mediated workflows (often used in low-bandwidth environments) may create additional risk through compression-only acquisitions and deterioration in explanation accuracy.[13] Adoption occurs in the context of both relational and workflow factors. Provider trust, perceived utility of the device, and time constraints can affect adoption for both formal PHC systems and informal community-based care.[1,12] Common solutions for facilitating adoption have included task shifting and re-designing workflows.[1] Trustworthy governance will be required prior to scaling of any device. Stakeholders identified informed consent, privacy literacy, transparency, and accountability as major barriers to responsible integration of AI into practices.[8] The gap between when a patient screens positive for a given condition (e.g., breast cancer screening) and when they actually receive care (i.e., a screening referral) represents a significant point of failure (referred to as "the screen-to-care gap"). Low referral adherence has limited the downstream clinical value of screening, indicating that in order to be successful with any implementation package, AI must come with systems for navigating referrals, tracking referrals through to closure, and providing socioeconomic support to patients.[5,6,10]

## Conclusion

In South Asian primary care settings, there are many interacting social-technical barriers to the use of AI-based diagnostic tools that include, but are not limited to, readiness of the infrastructure, level of trust from personnel, compatibility with workflows, ethical governance, ability to work across organizations and restrictions based on socio-economic factors. Future implementations should prioritize context-aware implementation design, physician training, task sharing, complete data governance frameworks to ensure data output translates into patient advantage, and enhanced completion of physician referrals for the use of AI-based diagnostic tools.

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## Conflict of Interest

All authors do not have any conflict of interest.

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## Author Contributions

Om Vaswani: Conceptualization, methodology, literature search, data charting, writing, original draft.

Muhammad Ahmed Abdullah: supervisor

Viveck Vasvani: Independent screening, writing review and editing.

Parkash: data verification

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