Review Article

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LEVERAGING AI TECHNOLOGY IN INTERPRETATION OF X-RAY IMAGES AND ITS INTEGRATION INTO THE PUBLIC HEALTH SYSTEM

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Abstract: Artificial Intelligence (AI) is increasingly used in chest X-ray (CXR) interpretation to improve the speed and scalability of screening in resource-constrained settings like India. This study systematically reviewed literature published after 2014, following PRISMA guidelines, to evaluate the diagnostic performance, cost, and efficiency of AI-assisted CXR interpretation compared to radiologists. Radiologists demonstrated an average sensitivity of 71.0% (95% CI: 68.0–76.2%) and specificity of 86.2% (95% CI: 84.0–87.8%), while AI showed higher sensitivity (86.8%; 95% CI: 81.5–90.4%) and comparable specificity (87.0%; 95% CI: 81.3–90.1%). Across prevalence levels relevant to India (0.5–5%), AI consistently yielded higher positive and negative predictive values, although PPV remained low at lower prevalence levels due to screening population characteristics. Sensitivity analyses indicated that AI reduced reporting time and costs under most scenarios, with variability depending on assumptions. AI demonstrates strong potential as a triage tool in large-scale screening programs such as tuberculosis under NTEP. However, its effectiveness depends on prevalence and implementation context. AI should be integrated as a complementary tool within existing workflows rather than a standalone replacement.

Key-words: AI diagnostics, Computer-aided detection, X-ray interpretation, Digital health

Introduction: Artificial Intelligence (AI) is rapidly transforming the future of public healthcare system. It has enabled faster analysis of medical data, supported large-scale disease screening with consistent and accurate diagnoses. It is becoming a powerful tool in medical imaging, especially for X-rays, CT scans, and MRIs, where it has shown strong diagnostic performance. Multiple studies have reported that integrating AI into the healthcare system have resulted in reduced reading time, faster disease detection, and improved overall workflow efficiency.

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AI in medical imaging works by learning from big database collections of medical images and identifying patterns that indicate abnormalities. Once AI is trained, it can rapidly analyze new images, highlight abnormalities, and provide consistent results. Unlike radiologists, whose performance may vary due to the level of experience, workload, or human error, AI delivers uniform screening across all cases and can process thousands of images without breaks. Another important advantage is that AI improves as it learns from more data, every new image strengthens its knowledge base. If AI assisted image reading is used widely into healthcare systems, its continuous learning can further improves its accuracy, and in the future, AI tools may improve with validated retraining on representative data, making them invaluable for disease detection and public health screening.

India faces a dual challenge of high disease burden and shortage of radiologists, creating significant barriers to timely and effective diagnosis of diseases like Tb and cancer in underserved areas1,2. India's tuberculosis (TB) control strategy has increasingly integrated digital diagnostics and artificial intelligence (AI) into routine screening pathways. Under the National TB Elimination Programme (NTEP), recent operational guidance supports the use of computer-aided detection (CAD) tools, such as CAD4TB and qXR, for triaging chest X-rays, particularly in high-burden and resource-constrained settings. This shift aligns with broader health system initiatives, including the Ayushman Bharat Pradhan Mantri Jan Arogya Yojana (PMJAY), which expands financial access to diagnostic imaging; the National Cancer Grid, which strengthens standardized imaging and reporting practices; and the Ayushman Bharat Digital Mission (ABDM) with platforms like eSanjeevani, which enable tele-radiology and remote interpretation. Together, these programmes signal a policy direction toward scalable, technology-enabled diagnostic ecosystems in India.

India's diagnostic capacity is constrained by uneven infrastructure and workforce distribution across regions. National assessments, including NITI Aayog reports on diagnostic capacity and the Ministry of Health's Rural Health Statistics, highlight gaps in access to imaging services, particularly in district and rural facilities. Policy analyses emphasize the need for scalable, technology-enabled solutions to address these gaps. NITI Aayog's frontier technology initiatives and digital health strategies underline the role of AI-enabled imaging and tele-radiology in improving access, reducing turnaround time, and strengthening diagnostic systems. In this context, leveraging AI within existing national programmes offers a pathway to enhance efficiency and equity in diagnostic service delivery across India.

In this study we aimed to conduct a systematic analysis of the use of AI technology in image interpretation for improved health outcomes in public health screening with a focus on its role in enhancing diagnostic accuracy, efficiency, and cost effectiveness.

PICO framework:

- Population (P): Individuals undergoing CXR for TB screening;
- Intervention (I): AI-assisted software tools for interpreting CXRs;
- Comparator (C): Human readers/ Radiologist;
- Outcomes (O): Sensitivity/specificity/PPV/NPV, time, cost;

Subjects and Methods: We conducted a systematic review using PRISMA guidelines. Databases searched included PubMed, Google Scholar, Arxiv, and WHO reports, government publications, and other relevant databases, the review included peer-reviewed articles, field studies, and reports published after 2014 with keywords like "AI in X-ray interpretation," "AI-assisted screening," "computer-aided detection," and "India".

Studies were included if they used AI or radiologist for image interpretation, reported diagnostic performance and Studies conducted after 2014. Exclusion criteria included studies focusing on non-image readings, or those lacking diagnostic performance data. Out of 47 identified studies/reports, 31 met the inclusion criteria as shown in Figure 1.

We extracted sensitivity and specificity values for radiologists (Conventional x-ray reporting) and AI from over 20 published studies (Table 3) and calculated simple arithmetic average of sensitivities/specificities across studies, for comparison. Diagnostic performance metrics were calculated by translated these arithmetic average sensitivity and specificity into counts of true positives (TP), false negatives (FN), false positives (FP) and true negatives (TN) using standard deterministic formulas for a screening cohort of size N at disease prevalence p ($0 \le p \le 1$). We present results for a cohort of N = 10,000 screened persons and showed scenario analysis for prevalences p = 0.5% ,1% ,2%, 3% and 5%. Results are rounded to two decimal counts for TP/FN/FP/TN and to two decimal percentage for PPV/NPV.

HTAIn have conducted a similar study comparing AI and Human Radiologist and they have found that cost per case for AI and radiologist are ₹22–30 and ₹100 respectively[3].

Cost inputs for AI-assisted chest X-ray interpretation were derived from the Health Technology Assessment in India (HTAIn) rapid assessment, which evaluated AI-based TB screening tools (qXR and Genki) in a programmatic public health screening context using a decision-tree modelling framework. The analysis reflects per-case costs (AI and radiologist are ₹22–30 and ₹100 respectively) under assumptions of screening workflows, throughput, and software licensing models specific to TB screening settings.

Given that HTAIn estimates are context-specific, one-way sensitivity analysis was conducted by varying radiologist costs (₹25–₹175 per case) and AI costs (₹15–₹45 per case) to reflect real-world variability across different healthcare settings. Radiologist reporting fees in India may vary widely (approximately ₹50–₹300 per case) depending on geography, service model (teleradiology vs in-house), and facility type.

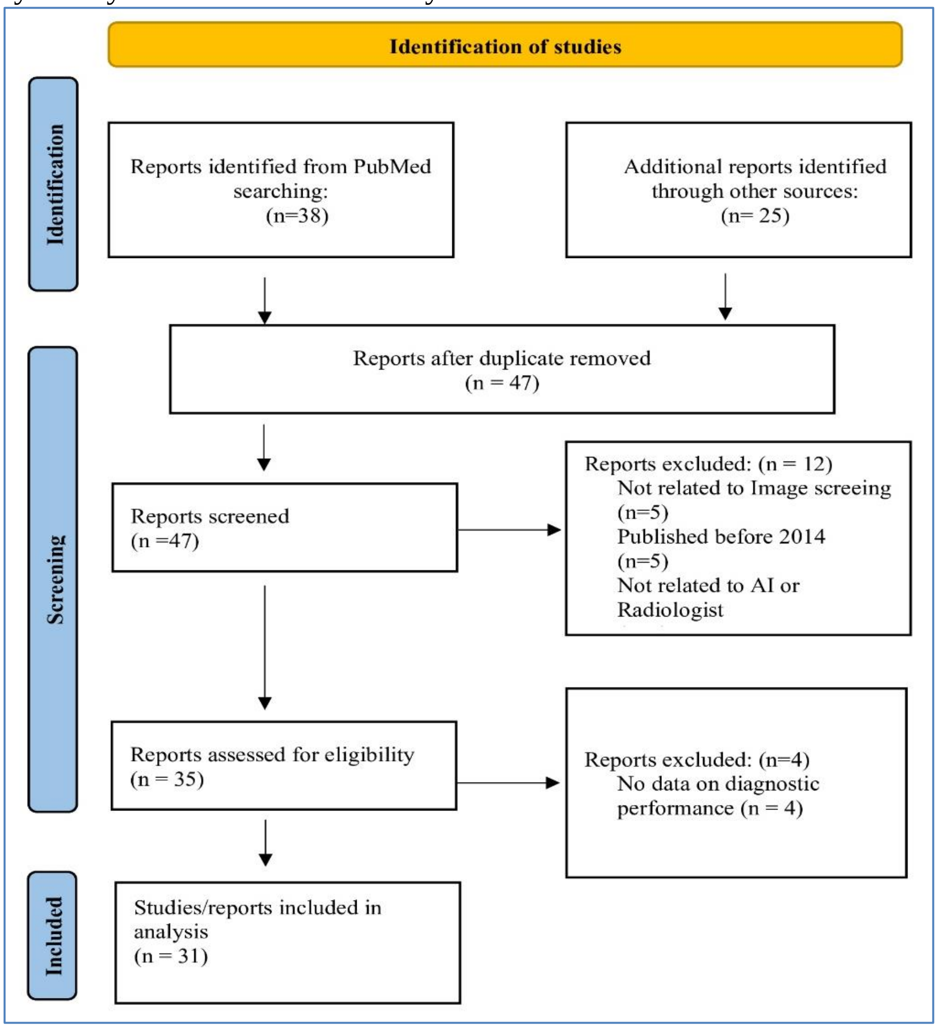

Figure 1: PRISMA flow diagram

For time assumptions, reporting durations were based on published literature indicating substantial variability in real-world practice. A base-case estimate of 2 minutes per case for radiologists and 1 minute for AI was used; however, this represents the higher (more conservative) end of ranges. Therefore, one-way sensitivity analysis was conducted by varying radiologist reporting time from 20 to 180 seconds and AI processing time from 10 to 90 seconds per case to assess the robustness of productivity outcomes

we have considered the same cost values as expressed by HTAIn for our analysis and these values were applied to a hypothetical cohort of 10,000 X-rays to estimate total expenditure and savings. Interpretation costs were estimated by multiplying per-case cost with total number of X-rays screened. The total time for 10,000 X-rays was

Indian Journal of Science and Research

Jain K. & Choudhury R.K., Ind. J. Sci. Res. 2026, 6(3), 143-154

then converted into 8-hour workdays (without breaks) to compare the workload between AI and radiologists.

Quality assessment and risk of bias: The methodological quality of the included studies was assessed using the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool. This tool evaluates risk of bias and applicability concerns across four domains: patient selection, index test, reference standard, and flow and timing. Each domain was rated as having low, high, or unclear risk of bias. The assessment was conducted by a single reviewer based on predefined criteria. The results were summarised and visualised using the robvis tool, which generates traffic light plots and summary figures to represent risk of bias and applicability concerns across studies.

Results: Quality assessment: The QUADAS-2 assessment indicated an overall low to moderate risk of bias across the included studies. Most studies demonstrated low risk of bias in the index test and reference standard domains, suggesting consistency in diagnostic evaluation. However, some concerns were noted in the patient selection domain, primarily due to non-random or selective sampling methods. Variability was also observed in the flow and timing domain across a subset of studies.

Applicability concerns were generally low for the index test and reference standard, while moderate concerns were observed in patient selection in some studies. The detailed risk of bias and applicability assessments are presented in the form of traffic light plots and summary graphs (Figure 2 and 3)

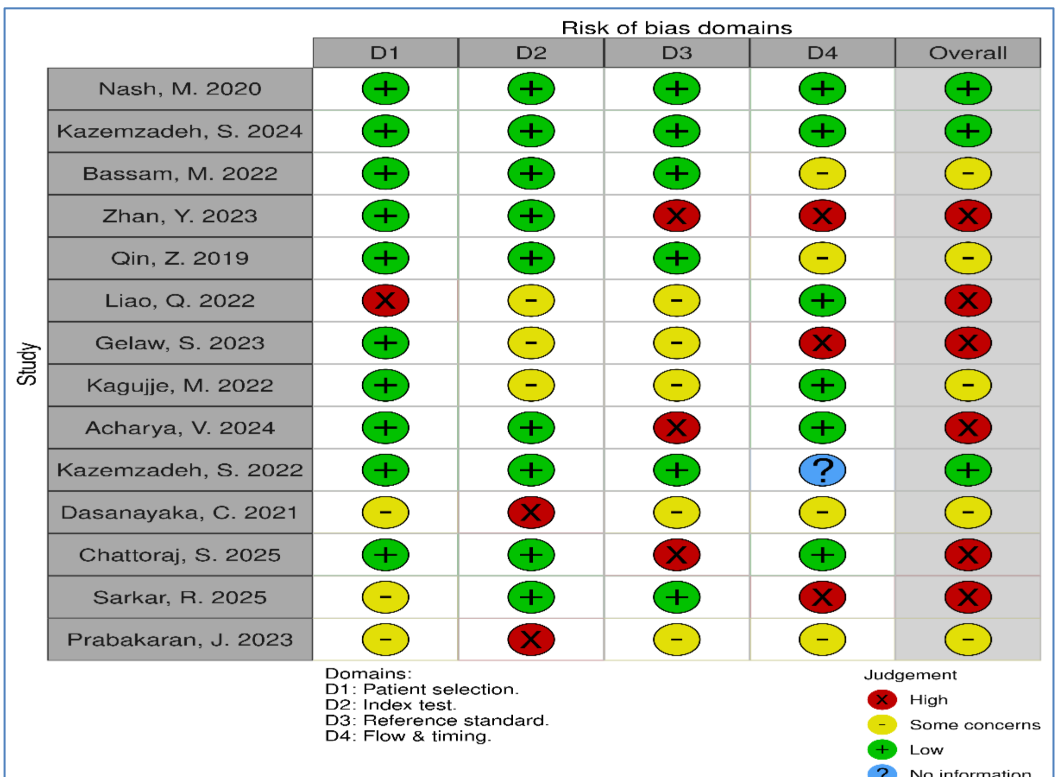

Figure 2. QUADAS-2 risk of bias assessment of included studies: Risk of bias was evaluated across four domains (D1–D4). Green indicates low risk, red high risk, yellow some concerns, and blue unclear. Overall study-level judgments are shown in the final column

Indian Journal of Science and Research

Jain K. & Choudhury R.K., Ind. J. Sci. Res. 2026, 6(3), 143-154

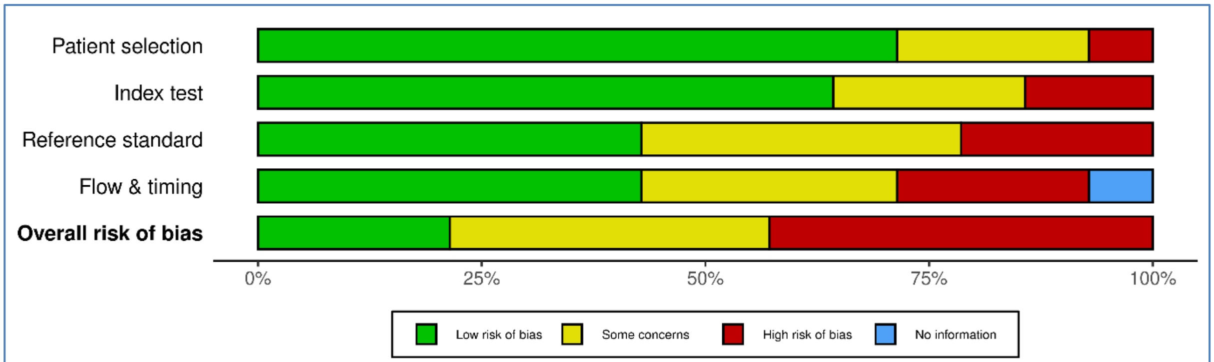

Figure 3. QUADAS-2 risk of bias summary: Bars represent the proportion of studies rated as low risk (green), some concerns (yellow), high risk (red), or unclear (blue) across each domain.

We extracted the sensitivities and specificities from the published literature and the simple arithmetic average analysis suggests that radiologists show an average sensitivity of 71% (95% Cl: 68% to 76%) and specificity of 86.2% (95% Cl: 84% to 87.8%), whereas AI-based systems showed a higher sensitivity of 86.8% (95% Cl: 81.5% to 90.4%) and specificity of 87% (95% Cl: 81.3% to 90.1%). These findings suggests that AI has good diagnostic performance and deliver results with high accuracy. Several studies have reported that when AI-assisted screening is combined with radiologist's interpretation, the performance can exceed 90% of sensitivity and specificity, showcasing the strong potential for such hybrid models in clinical practice.

	AI		**Radiologist**	
Prevalence	PPV (95% Cl)	NPV (95% Cl)	PPV (95% Cl)	NPV (95% Cl)
0.50%	**3.24%** (95% Cl: 2.14% to 4.39%)	**99.92%** (95% Cl: 99.89% to 99.95%)	**2.52%** (95% Cl: 2.09% to 3.04%)	**99.83%** (95% Cl: 99.81% to 99.86%)
1%	**6.31%** (95% Cl: 4.22% to 8.44%)	**99.85%** (95% Cl: 99.77% to 99.89%)	**4.94%** (95% Cl: 4.12% to 5.93%)	**99.66%** (95% Cl: 99.62% to 99.73%)
2%	**11.99%** (95% Cl: 8.17% to 15.71%)	**99.69%** (95% Cl: 99.54% to 99.78%)	**9.50%** (95% Cl: 7.98% to 11.31%)	**99.32%** (95% Cl: 99.23% to 99.45%)
3%	**17.11%** (95% Cl: 11.88% to 22.02%)	**99.53%** (95% Cl: 99.30% to 99.67%)	**13.73%** (95% Cl: 11.62% to 16.19%)	**98.97%** (95% Cl: 98.84% to 99.17%)
5%	**26.00%** (95% Cl: 18.66% to 32.46%)	**99.21%** (95% Cl: 98.82% to 99.44%)	**21.31%** (95% Cl: 18.28% to 24.74%)	**98.26%** (95% Cl: 98.03% to 98.59%)

Table 1: PPV and NPV across prevalence levels for AI and radiologist; Values are presented as estimates with ranges derived from the 95% confidence intervals of sensitivity and specificity.

Indian Journal of Science and Research
Jain K. & Choudhury R.K., Ind. J. Sci. Res. 2026, 6(3), 143-154

When predictive values were examined across various disease prevalence levels, AI consistently maintained higher Positive Predictive Value (PPV) and Negative Predictive Value (NPV) compared to radiologists (Table 1).

Prevalence	Diseased	Non-Diseased	AI_TP	AI_FN	AI_TN	AI_FP
0.50%	50	9950	43.40	6.60	8656.50	1293.50
1%	100	9900	86.80	13.20	8613.00	1287.00
2%	200	9800	173.60	26.40	8526.00	1274.00
3%	300	9700	260.40	39.60	8439.00	1261.00
5%	500	9500	434.00	66.00	8265.00	1235.00

Table 2: Table 2: Diagnostic performance matrix of AI (TP, TN, FP, and FN)

The diagnostic performance matrix (Table 2 & 3) revealed that AI can identify a higher number of true positives compared to radiologists, while also maintaining a greater count of true negatives across different prevalence levels.

Prevalence	Diseased	Non-Diseased	AI_TP	AI_FN	AI_TN	AI_FP
0.50%	50	9950	35	14	8576	1373
1%	100	9900	71	29	8533	1366
2%	200	9800	142	58	8447	1352
3%	300	9700	213	87	8361	1338
5%	500	9500	355	145	8189	1311

Table 3: Table 2: Diagnostic performance matrix of Radiologist (TP, TN, FP, and FN)

This overall pattern highlights that AI is not only highly sensitive in detecting true cases but also more reliable in ruling out disease.

The one-way sensitivity analysis demonstrated that cost outcomes were sensitive to variations in radiologist reporting fees. AI-assisted interpretation remained cost-saving when radiologist costs exceeded approximately ₹30 per case, while at very low radiologist costs (e.g., ₹25), AI was no longer cost-saving. Across the examined AI cost range (₹15–₹45 per case), AI remained cost-saving, although the magnitude of savings decreased as AI costs increased. These findings reflect the substantial variability in radiologist fees in India and indicate that cost-effectiveness is primarily driven by local pricing structures.

Sensitivity analysis of reporting time assumptions showed that productivity gains varied depending on reporting durations. The base-case assumption of 2 minutes per radiologist read represents a conservative estimate within the range reported in literature, thereby favouring AI in the base scenario. When radiologist reporting time was reduced, the productivity advantage of AI decreased, whereas longer reporting times increased the relative benefit of AI. Similarly, increases in AI processing time reduced its relative advantage. Across all plausible ranges examined, AI consistently reduced total reporting time compared to radiologist-only workflows, although the magnitude of reduction varied, indicating that productivity estimates should be interpreted as a range rather than a fixed value.

Indian Journal of Science and Research

Jain K. & Choudhury R.K., Ind. J. Sci. Res. 2026, 6(3), 143-154

Paper Title	Year	population	Location	Tech	Rad Sn	Rad Sp	AI sn	AI sp	AUC
Nash, M., *et al.*, 2020	2020	929	India (Mumbai)	qXR, Qure.ai	56% (95% CI: 50%, 62%)	80% (95% CI: 77%, 83%)	71% (95% CI: 66%, 76%)	80% (95% CI: 77%, 83%)	microbiologically-confirmed PTB: 0.81 (95% CI: 0.78, 0.84) pleural effusion: AUC of 0.94 (95% CI: 0.92, 0.96) cavity: 0.84 (95% CI: 0.82, 0.87)
Kazemzadeh, S., *et al.*, 2024	2024	1910	Zambia (Chawama, Kanyama, and Chainda)	Cloud-based AI tools	87% [95% CI, 82 to 92]	70% [95% CI, 67 to 72]	76% (95% CI, 71 to 83)	82% (95% CI, 77 to 85)	TB: 0.87 (95% CI: 0.84, 0.90) Abnormality: 0.97 (95% CI: 0.96, 0.98)
Bassam, M., *et al.*, 2022	2022	13,426	45 Locations world Wide	qXR, Qure.ai	75% [95% CI, 74 to 76]	99% [95% CI, 98 to 99]	99% [95% CI, 95 to 100]	90% [95% CI, 87 to 92]	Malignant Nodule: 0.99 (95% CI: 0.98, 0.99)
Zhan, Y., *et al.*, 2023	2023	1,24,959	China				93% (95% CI 87–96%)	94% (95% CI 90–97%)	
Qin, Z., *et al.*, 2019	2019	1196	Nepal and Cameroon	CAD4TB, Lunit INSIGHT, and qXR			89% (95% CI 87–91%)	88% (95% CI 84–89%)	Lunit (0.94, 95% CI: 0.93–0.96) qXR (0.94, 95% CI: 0.92–0.97) CAD4TB (0.92, 95% CI: 0.90–0.95)
Liao, Q., *et al.*, 2022	2022	2,543	China	AI-based CAD system	62% [95% CI, 60 to 75]	98% [95% CI, 96 to 99]	75% (95% CI 73–77%)	97% (95% CI 94–99%)	AI: (0.85, 95% CI: 0.83–0.86) Radiologist: (0.85, 95% CI: 0.83–0.86)
Gelaw, S., *et al.*, 2023	2023	1769	--	CAD4TB v6, Lunit INSIGHT v4.9.0, and qXR v2			82% (95% CI 80–84%)	84% (95% CI 82–86%)	Lunit (0.87, 95% CI: 0.85–0.88) qXR (0.81, 95% CI: 0.80–0.83) CAD4TB (0.87, 95% CI: 0.86–0.89)

Indian Journal of Science and Research

Jain K. & Choudhury R.K., Ind. J. Sci. Res. 2026, 6(3), 143-154

Kagujje, M., *et al.*, 2022	2022	1884	--	CAD4TB (v.7.0) qXR (v.3.0)			90% (95% CI: 85.1–93.2%)	61.8% (95% CI: 58.9–64.5%)	
Acharya, V., *et al.*, 2024	2024		India	CAD			92% [95% CI, 99 to 95]	98% [95% CI, 94 to 99]	0.99 (95% CI: 0.98, 0.99)
Kazemzadeh, S., *et al.*, 2022	2022	165 754	China, India, the United States, and Zambia	DLS	75% [95% CI, 74 to 76]	84% (95% CI 82–86%)	88% (95% CI 87–91%)	79% (95% CI 74–91%)	AI: 0.89 (95% CI: 0.87, 0.91)
Dasanayaka, C., *et al.*, 2021	2021		India				98% [95% CI, 94 to 99]	96% (95% CI 94–98%)	AI: 0.97 (95% CI: 0.96, 0.98)
Chattoraj, S., *et al.*, 2025	2025	10000	India	qXR, Qure.ai			0.831 (95% CI: 0.740–0.895)	0.826 (95% CI: 0.782–0.904)	AI: 0.94 (95% CI: 0.90–0.97)
Sarkar, R., *et al.*, 2025	2025		India				92% (62.9-98.7%)	98.2% (68.4-99.9%)	
Prabakaran, J., *et al.*, 2023	2023	79462	India, Tamil Nadu	CXR-AI			0.98 (95%, CI: 0.97, 0.98)	0.96 (95% CI: 0.96, 0.97)	

Table 4: Diagnostic performance of AI and radiologist-based chest X-ray interpretation across included studies. Sn: Sensitivity; Sp: Specificity; AUC: Area under the curve; CAD: Computer-aided detection; CAD4TB: Computer-aided detection for tuberculosis; DLS: Deep learning system; qXR: Qure.ai chest X-ray AI tool; Lunit INSIGHT: AI-based chest radiography analysis system; CXR-AI: Artificial intelligence-based chest X-ray interpretation system; PTB: Pulmonary tuberculosis; CI: Confidence interval.

Discussion: The findings of this study need to be interpreted in the context of India's TB screening strategies and varying disease prevalence. At low prevalence levels (0.5–1%), which correspond to symptomatic screening under the National TB Elimination Programme (NTEP), both AI and radiologists demonstrate very high negative predictive value (>99%), indicating strong ability to rule out disease. However, AI shows consistently higher positive predictive value compared to radiologists, suggesting improved identification of true TB cases even in low-prevalence settings. At higher prevalence levels (2–5%), typical of active case-finding in vulnerable populations, the advantage of AI becomes more pronounced, with higher true positive detection and improved PPV.

The performance observed in this review aligns with evidence from Indian field settings. Studies such as Nash *et al*. (2020) from Manipal and Vijayan *et al*. (2023) from Maharashtra have demonstrated that AI-based chest X-ray interpretation achieves performance comparable to or exceeding that of radiologists in real-world programmatic environments. Deployments of AI tools such as qXR, DeepTek, and other commercially available systems in India have further demonstrated feasibility in high-volume screening settings. Compared to global estimates (Nepal and Cameroon reported high performance, with AUCs ranging between 0.92 and 0.94. Similarly, other global studies also confirmed that different AI tools have met the WHO target of ≥ 70% specificity at 90% sensitivity), the diagnostic performance observed in this review is consistent, but importantly confirms that such performance is achievable within Indian public health systems, including resource-constrained and high-burden settings.

These findings should be interpreted alongside existing policy and programmatic guidance. The Government of India, through NTEP operational guidelines (2021 onwards), has already endorsed the use of computer-aided detection (CAD) tools such as CAD4TB and qXR for TB triage. Similarly, the World Health Organization (WHO) in 2021 recommended CAD as an alternative to human readers for TB screening in individuals aged ≥15 years. While the HTAIn (2023) rapid assessment concluded that AI-assisted chest X-ray interpretation can be cost-effective in TB screening settings, it was based on specific assumptions related to public-sector workflows and limited scenarios. The present study builds upon this by integrating diagnostic performance, predictive values across multiple prevalence scenarios, and sensitivity analyses for cost and time, thereby providing a relevant assessment for Indian screening programs.

India's evolving digital health ecosystem further strengthens the case for AI integration. Platforms under the Ayushman Bharat Digital Mission (ABDM), along with telemedicine services such as eSanjeevani, enable large-scale deployment of AI-supported diagnostic workflows. Teleradiology networks, including those operated by private providers and AI-enabled platforms (e.g., Qure.ai, DeepTek, and similar systems), have already demonstrated the feasibility of remote interpretation and scalable screening. In this context, AI can act as a first-line triage tool, enabling prioritisation of abnormal cases and reducing reporting burden in high-volume settings.

However, several implementation challenges must be considered. First, the regulatory landscape for AI-based diagnostic tools in India is still evolving, with oversight by CDSCO and varying international approvals (e.g., CE marking, FDA clearance). Second, concerns related to algorithmic bias and generalisability remain important, particularly across diverse Indian sub-populations such as paediatric, elderly, or high-risk occupational groups. Third, data governance and patient privacy under frameworks such as the Digital Personal Data Protection (DPDP) Act, 2023 must be addressed when deploying AI at scale. Finally, integration of AI into clinical workflows requires training of frontline healthcare workers, including radiographers and medical officers, to appropriately interpret and act on AI outputs.

Overall, while AI demonstrates clear advantages in sensitivity, efficiency, and scalability, its role should be viewed as augmentative rather than substitutive.

The results of this study suggest that AI can enhance screening efficiency and case detection within India's public health programs, but its impact will depend on appropriate integration within existing systems, regulatory oversight, and continued evaluation in real-world settings.

Limitation: This study has several limitations. First, the analysis relies on simple arithmetic averaging of sensitivity and specificity across studies, without weighting for study size, assessment of heterogeneity (e.g., I^2, τ^2), or use of bivariate/HSROC meta-analytic models. As a result, the pooled estimates should be interpreted as descriptive rather than statistically derived summary measures. Second, there is substantial heterogeneity in the AI systems included in the analysis. Different tools (e.g., qXR, CAD4TB, Lunit INSIGHT CXR, and others) vary in underlying algorithms, training datasets, and deployment settings. Pooling these as a single "AI" category may mask important differences in performance across products. Third, the study was not prospectively registered (e.g., in PROSPERO), and therefore methodological decisions were not externally documented prior to data extraction. Fourth, many included studies were conducted in controlled or pilot environments rather than routine programmatic settings, which may limit generalisability to real-world public health implementation, particularly in rural or resource-constrained areas. Fifth, variability in study populations, disease prevalence, and imaging quality across included studies introduces additional uncertainty. Although ranges were incorporated using reported confidence intervals, formal heterogeneity analysis was not performed. Sixth, the estimation of predictive values (PPV and NPV) is based on modelled prevalence scenarios and average diagnostic performance, rather than individual patient-level data, and should therefore be interpreted as indicative rather than definitive. Seventh, cost estimates were derived from HTAIn and applied to a hypothetical cohort, and may not fully capture real-world variations in pricing, licensing models, infrastructure costs, and operational workflows across different healthcare settings in India. Finally, while this study incorporates uncertainty through one-way sensitivity analyses, it does not include probabilistic sensitivity analysis, which may further refine uncertainty estimation in future work.

Conclusion: AI-assisted image interpretation represents huge potential for India's public health system. By combining the imaging infrastructure with the speed, consistency, and accuracy of AI, healthcare programs can achieve earlier disease detection, reduce the burden on human experts, and bridge diagnostic gaps in underserved regions. AI-assisted image interpretation can expand coverage, improve consistency, and accelerate case detection, all while keeping costs manageable.

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Contribution Details:

	Corresponding Author	Author 2
Concepts	✓	✓
Design	✓	✓
Definition of intellectual content	✓	✓
Literature search	✓	✓
Data acquisition	✓	✓
Data analysis	✓	✓
Statistical analysis	✓	✓
Manuscript preparation	✓	✓
Manuscript editing	✓	✓
Manuscript review	✓	✓

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