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Impact of AI-Assisted Chest Radiography as a Triage Tool for Molecular Lab Testing in Rural Philippines: A Systematic Review of Diagnostic Yield and Health Equity

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ABSTRACT

Artificial intelligence (AI)–assisted chest radiography has increasingly been utilized as a diagnostic triage tool for tuberculosis (TB) screening and molecular laboratory testing in resource-limited healthcare settings. In the Philippines, limited access to radiologists, molecular diagnostic facilities, and healthcare infrastructure in rural and geographically isolated communities continues to contribute to delayed TB diagnosis and treatment. AI-assisted chest radiography may improve diagnostic efficiency, optimize molecular testing utilization, and strengthen equitable access to healthcare services. This systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines and was registered in PROSPERO under registration number: CRD420261395186. A comprehensive literature search was conducted across PubMed/MEDLINE, Scopus, and Web of Science, supplemented by manual searches of institutional and organizational reports. Studies published between January 2019 and March 2026 were screened according to predefined inclusion and exclusion criteria. Eligible studies evaluated AI-assisted chest radiography as a screening or triage tool for molecular diagnostic testing in rural or resource-limited settings. Data was synthesized narratively. Thirty-three studies met the inclusion criteria. The findings demonstrated that AI-assisted chest radiography consistently achieved high sensitivity for TB screening and effectively functioned as a triage mechanism for molecular diagnostic testing including GeneXpert, Truenat, and PCR assays. Several studies reported improved diagnostic yield, reduced unnecessary molecular testing, enhanced workflow efficiency, and improved treatment linkage. Portable AI-assisted chest X-ray systems also demonstrated operational feasibility in geographically isolated and disadvantaged communities. However, variability in specificity, screening thresholds, infrastructure readiness, and implementation capacity across healthcare settings remained important challenges. AI-assisted chest radiography represents a promising strategy for strengthening TB diagnostic pathways, optimizing molecular laboratory utilization, and improving equitable access to diagnostic services in resource-constrained healthcare settings. Further prospective implementation studies, cost-effectiveness analyses, and health systems evaluations are needed to support large-scale integration of AI-assisted diagnostic technologies within Philippine healthcare systems.

Keywords: artificial intelligence, chest radiography, tuberculosis, molecular diagnostic testing, GeneXpert, diagnostic yield, health equity, rural healthcare, computer-aided detection, Philippines

INTRODUCTION

Artificial intelligence (AI) has emerged as one of the most rapidly advancing technologies in modern healthcare, particularly within the field of medical imaging. AI in radiology refers to the application of machine learning and deep learning algorithms capable of analyzing radiologic images and identifying disease-related abnormalities with minimal human intervention (Hosny et al., 2018). In chest radiography, AI systems are trained using large datasets of labeled chest X-ray images to recognize pathologic findings such as pulmonary infiltrates, nodules, consolidations, and cavitary lesions commonly associated with respiratory diseases including tuberculosis (TB) and pneumonia (Esteva et al., 2019; Pesapane et al., 2018). These technologies are increasingly integrated into healthcare systems as clinical decision-support tools that assist healthcare professionals in image interpretation, prioritization of high-risk cases, and facilitation of early diagnostic evaluation (Hanna et al., 2025).

AI-assisted chest radiography systems may function in different capacities within diagnostic pathways. Detection algorithms are primarily designed to identify radiologic abnormalities suggestive of disease, while triage algorithms prioritize patients according to the likelihood of clinically significant findings and recommend additional diagnostic testing when necessary (Gu et al., 2026; Strubchevska et al., 2024). Diagnostic support systems may also generate probability scores or classification outputs that support radiologists and clinicians in clinical decision-making (Rajpurkar et al., 2017; Topol, 2019). In recent years, AI-assisted chest radiography has increasingly been applied in infectious disease screening programs, particularly for pulmonary tuberculosis, where it serves as a triage tool to determine which individuals should undergo confirmatory molecular laboratory testing such as polymerase chain reaction (PCR), GeneXpert, and Truenat assays (Geric et al., 2023).

Tuberculosis remains a major global public health challenge and continues to disproportionately affect low- and middle-income countries where access to diagnostic services remains limited (World Health Organization, 2026). Early detection and rapid initiation of treatment are essential components of TB control strategies because delayed diagnosis contributes to continued disease transmission, poor clinical outcomes, and increased mortality (Cole et al., 2020). Molecular diagnostic tests such as Xpert MTB/RIF and other nucleic acid amplification tests have substantially improved TB diagnosis because of their high sensitivity and rapid turnaround time (Feng et al., 2025). However, access to these molecular diagnostic technologies remains uneven in many resource-constrained healthcare systems due to financial limitations, inadequate laboratory infrastructure, and shortages of trained personnel (World Health Organization, 2021).

Within this context, AI-assisted chest radiography has gained attention as a potentially scalable and cost-effective triage strategy capable of optimizing molecular laboratory utilization while improving diagnostic access in underserved settings (Raval et al., 2025). The integration of artificial intelligence into diagnostic and laboratory workflows has also demonstrated significant potential for improving diagnostic accuracy, operational efficiency, and clinical decision-making across diverse healthcare settings (Melford & O'Brien-Melford, 2026). The diagnostic performance of AI-assisted chest radiography is commonly evaluated using measures such as sensitivity, specificity, positive predictive value, negative predictive value, and area under the receiver operating characteristic curve (AUC) (Essa, 2025; Castilla et al., 2025). Additional implementation outcomes including diagnostic yield, workflow efficiency, cost-effectiveness, and reduction in unnecessary molecular testing are also important in evaluating the clinical utility of AI-assisted screening systems (Kelly et al., 2019). Diagnostic yield is particularly relevant in triage-oriented healthcare settings because it reflects the proportion of confirmed disease cases identified among individuals referred for molecular laboratory testing following AI-assisted screening (Marquez et al., 2025).

The integration of AI-assisted imaging technologies into healthcare systems may provide important benefits in low-resource settings characterized by shortages of radiologists and unequal access to healthcare services. Many low- and middle-income countries continue to face substantial gaps in diagnostic imaging infrastructure and specialist workforce distribution, resulting in delayed diagnosis and limited access to timely healthcare interventions (Frija et al., 2021). Automated chest radiograph interpretation systems may therefore support frontline healthcare providers by facilitating rapid identification of presumptive TB cases and prioritization of patients requiring confirmatory molecular testing, particularly in areas where radiologists are unavailable (World Health Organization, 2021).

These challenges are particularly relevant in the Philippines, where healthcare access remains highly uneven across urban, rural, and geographically isolated communities (Panganiban et al., 2024). Rural healthcare facilities frequently lack radiologists, advanced imaging technologies, and accessible molecular diagnostic laboratories, thereby contributing to delays in TB diagnosis and treatment initiation (Alberto et al., 2022). Molecular diagnostic services are often concentrated in urban referral centers and centralized laboratories, limiting accessibility for individuals residing in geographically isolated and disadvantaged areas (Department of Health Philippines, 2023; World Health Organization [WHO], 2018). Consequently, healthcare disparities continue to affect the efficiency of TB detection and disease management in underserved Philippine communities.

In response to these healthcare delivery challenges, AI-assisted chest radiography has emerged as a promising approach for strengthening TB screening and diagnostic triage pathways within rural and resource-constrained settings. Portable digital chest X-ray systems integrated with AI-powered computer-aided detection (CAD) software now enable rapid point-of-care screening and identification of presumptive TB cases even in geographically isolated communities (Yacat, 2024; Macpherson et al., 2025). Several implementation initiatives in the Philippines have demonstrated the operational feasibility of combining AI-assisted chest radiography with mobile molecular testing platforms such as GeneXpert and Truenat systems to improve diagnostic accessibility and reduce delays in care (Stop TB Partnership, 2024; University Research Co., 2024). These developments suggest that AI-assisted radiographic triage may strengthen healthcare delivery by optimizing molecular testing pathways and improving access to diagnostic services in underserved populations.

Despite growing international interest in AI-assisted radiologic diagnostics, existing evidence remains fragmented regarding its real-world impact on diagnostic yield, laboratory utilization, workflow efficiency, and health equity in resource-limited healthcare settings (Flores et al., 2025). Much of the available literature has focused primarily on technical algorithm development and diagnostic accuracy validation under controlled conditions rather than evaluating the broader implementation and public health implications of integrating AI-assisted chest radiography into routine healthcare delivery systems. Furthermore, limited synthesized evidence currently exists regarding the use of AI-assisted chest radiography specifically as a triage tool for molecular laboratory testing within the Philippine healthcare context (Marquez et al., 2025).

Although several international studies have demonstrated promising diagnostic performance of AI-assisted chest radiography systems, important concerns remain regarding variability in screening thresholds, healthcare infrastructure readiness, algorithmic bias, data governance, and equitable deployment in low-resource healthcare systems (Hwang et al., 2024). In addition, evidence regarding the operational effectiveness and public health impact of AI-assisted diagnostic triage in geographically isolated and disadvantaged communities remains limited. Understanding how these technologies influence diagnostic pathways and healthcare accessibility is therefore essential for informing evidence-based digital health strategies and national TB control programs.

Given these gaps in the literature, a comprehensive synthesis of available evidence is necessary to better understand the role of AI-assisted chest radiography in strengthening molecular diagnostic pathways and promoting equitable access to healthcare services in underserved communities. Evaluating its impact on diagnostic yield, workflow efficiency, and laboratory utilization is particularly important in settings where healthcare resources remain constrained and diagnostic capacity is limited.

Therefore, this systematic review aimed to evaluate the impact of AI-assisted chest radiography as a triage tool for molecular laboratory testing in rural healthcare settings in the Philippines and comparable resource-limited settings. Specifically, the study aimed to: (1) assess the diagnostic yield of AI-assisted chest radiography in identifying patients requiring molecular testing; (2) examine the effectiveness of AI-based radiographic triage in optimizing molecular laboratory testing pathways; and (3) evaluate the implications of AI-assisted diagnostic triage for improving health equity and access to diagnostic services in rural and underserved communities.

METHODOLOGY

Study Design

This study was conducted as a systematic review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to synthesize available evidence regarding the use of artificial intelligence (AI)–assisted chest radiography as a triage tool for molecular laboratory testing and its implications for diagnostic yield, workflow optimization, and health equity in rural and resource-limited healthcare settings. The review aimed to identify, evaluate, and synthesize published literature examining how AI-supported chest radiographic interpretation influences diagnostic pathways and utilization of molecular laboratory testing in underserved populations. The review protocol was registered in the International Prospective Register of Systematic Reviews (PROSPERO) under registration number: CRD420261395186.

Information Sources and Search Strategy

A comprehensive literature search was conducted across three major electronic databases: PubMed/MEDLINE, Scopus, and Web of Science. These databases were selected because they provide broad coverage of biomedical, radiologic, public health, and digital health research relevant to artificial intelligence and diagnostic imaging. Additional studies were identified through manual screening of reference lists from included articles as well as institutional reports, programmatic publications, and organizational documents related to AI-assisted chest radiography, tuberculosis screening, and molecular diagnostic implementation.

The search strategy combined controlled vocabulary terms and free-text keywords related to artificial intelligence, chest radiography, tuberculosis screening, molecular diagnostics, and rural healthcare delivery. An example of the search strategy used in PubMed included the following terms: ("artificial intelligence" OR "machine learning" OR "deep learning" OR AI OR "computer-aided detection") AND ("chest radiography" OR "chest X-ray" OR radiography) AND (triage OR screening OR "case finding") AND ("molecular testing" OR PCR OR GeneXpert OR Truenat OR "molecular diagnosis") AND ("tuberculosis" OR TB) AND ("rural health" OR "resource-limited settings" OR "low-resource settings" OR Philippines). Equivalent Boolean operators and indexing terms were adapted for Scopus and Web of Science to ensure consistent retrieval of relevant studies across databases. Only studies published in English between January 2019 and March 2026 were considered for inclusion to capture recent developments in AI-assisted medical imaging and molecular diagnostic technologies.

Eligibility Criteria

Eligibility criteria were developed using the Population, Intervention, Comparator, Outcomes, and Study Design (PICOS) framework. Studies were included if they evaluated AI-assisted chest radiography, computer-aided detection systems, or deep learning–based chest X-ray interpretation tools used in clinical screening or triage settings. Eligible studies were required to examine the role of AI-based radiographic interpretation in guiding subsequent molecular diagnostic testing, including polymerase chain reaction (PCR), Xpert MTB/RIF, GeneXpert, Truenat, or other nucleic acid amplification tests. Studies reporting diagnostic outcomes such as sensitivity, specificity, area under the receiver operating characteristic curve (AUC), diagnostic yield, workflow efficiency, or healthcare accessibility outcomes were included in the review.

Studies conducted in rural, resource-limited, community-based, or low-resource healthcare settings were prioritized because of the review's focus on health equity and diagnostic accessibility. Original research articles, implementation studies, operational studies, and credible institutional or programmatic reports published in peer-reviewed or publicly accessible sources were eligible for inclusion.

Studies were excluded if they were review articles, editorials, commentaries, conference abstracts, or letters without primary findings. Studies focusing solely on algorithm development without clinical or implementation evaluation were also excluded. Additionally, studies that did not involve chest radiography, molecular diagnostic pathways, or relevant diagnostic and implementation outcomes were excluded from the review.

Study Selection

All retrieved records were exported into a reference management software program, and duplicate records were removed prior to screening. Titles and abstracts of identified studies were independently screened according to the predefined eligibility criteria to determine relevance to the research objectives. Full-text articles of potentially eligible studies were subsequently retrieved and assessed for final inclusion in the systematic review. Disagreements encountered during the screening and selection process were resolved through discussion and consensus among the reviewers.

The study selection process was documented using a PRISMA 2020 flow diagram. A total of 185 records were initially identified through database searches and additional sources. After removal of duplicate records, 143 studies underwent title and abstract screening. Following eligibility assessment, 33 studies met the inclusion criteria and were included in the final narrative synthesis.

Data Extraction

Data from the included studies were extracted using a standardized data extraction form developed specifically for this review. Extracted information included the first author, year of publication, country or region of study, study design, healthcare setting, sample population, type of AI system or software evaluated, imaging modality used, molecular diagnostic method employed, and reported diagnostic performance outcomes including sensitivity, specificity, and AUC. Additional information related to diagnostic yield, workflow efficiency, implementation feasibility, operational outcomes, healthcare accessibility, and implications for health equity was also extracted where available. The extracted data were organized into structured evidence tables to facilitate systematic comparison and synthesis of findings across included studies.

Quality Assessment and Risk of Bias

The methodological quality and risk of bias of included diagnostic accuracy studies were assessed using the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool. The QUADAS-2 tool evaluates methodological quality across four domains: patient selection, index test, reference standard, and flow and timing. Each included study was assessed according to these domains to determine the reliability, validity, and applicability of the reported diagnostic performance outcomes. Implementation and operational studies that were not strictly diagnostic accuracy studies were additionally evaluated narratively according to methodological clarity, reporting completeness, implementation relevance, and consistency of outcome reporting.

Data Synthesis

A narrative synthesis approach was employed because substantial heterogeneity existed across study designs, AI software platforms, screening thresholds, healthcare settings, implementation models, and reported outcome measures. Quantitative meta-analysis was not performed due to variability in methodologies and inconsistency in reporting diagnostic outcomes among included studies. The findings were synthesized according to key thematic domains, including diagnostic accuracy and validation of AI-assisted chest radiography, diagnostic yield and optimization of molecular testing pathways, implementation feasibility and operational outcomes, healthcare access and health equity implications, and digital health infrastructure and workflow optimization. Where comparable diagnostic performance measures were available, findings related to sensitivity, specificity, AUC, and reductions in molecular testing utilization were summarized descriptively across studies.

Ethical Considerations

This study involved the review and synthesis of previously published literature and publicly accessible reports and did not involve direct participation of human subjects, collection of identifiable personal information, or patient intervention. Therefore, formal ethical approval from an institutional review board or ethics committee was not required.

The review was conducted in accordance with principles of academic integrity, transparency, and responsible research reporting. All included studies were appropriately cited and acknowledged to ensure proper attribution of original findings and avoidance of plagiarism. Ethical considerations related to the implementation of artificial intelligence in healthcare, including algorithmic bias, equitable access to diagnostic technologies, digital health disparities, and responsible deployment of AI systems in resource-limited healthcare settings, were also considered during interpretation and discussion of findings.

Reporting Standards

This systematic review was conducted and reported in accordance with the PRISMA 2020 guidelines for systematic reviews. A completed PRISMA checklist and PRISMA flow diagram were prepared and included as supplementary materials to improve transparency, reproducibility, and reporting quality of the review process.
Figure 1. PRISMA flow diagram showing the study selection process for the systematic review on AI-assisted

chest radiography as a triage tool for molecular laboratory testing in rural Philippine healthcare settings. Records were identified through electronic database searches in PubMed/MEDLINE, Scopus, and Web of Science. Additional records were identified through manual screening of reference lists, institutional reports, programmatic documents, and relevant organizational publications related to AI-assisted chest radiography, tuberculosis screening, and molecular diagnostic testing.

A total of 185 records were identified. Of these, 160 records were obtained from database searches and 25 records were identified through additional sources. After removal of 42 duplicate records, 143 records remained for title and abstract screening. During screening, 82 records were excluded because they were not directly related to AI-assisted chest radiography, molecular diagnostic testing, tuberculosis screening, rural healthcare, or health equity. A total of 61 full-text records were assessed for eligibility. Of these, 28 records were excluded. Reasons for exclusion included review articles or commentaries not presenting primary findings, studies focused only on algorithm development without clinical or programmatic evaluation, studies not involving chest radiography, studies without molecular diagnostic confirmation or diagnostic pathway outcomes, and studies not relevant to rural or resource-limited healthcare settings. Finally, 33 studies met the inclusion criteria and were included in the systematic review. These studies were synthesized narratively according to diagnostic accuracy and performance, implementation and programmatic outcomes, diagnostic infrastructure and digital health relevance, cost-effectiveness or modelling evidence, and broader AI-assisted radiology workflow optimization.

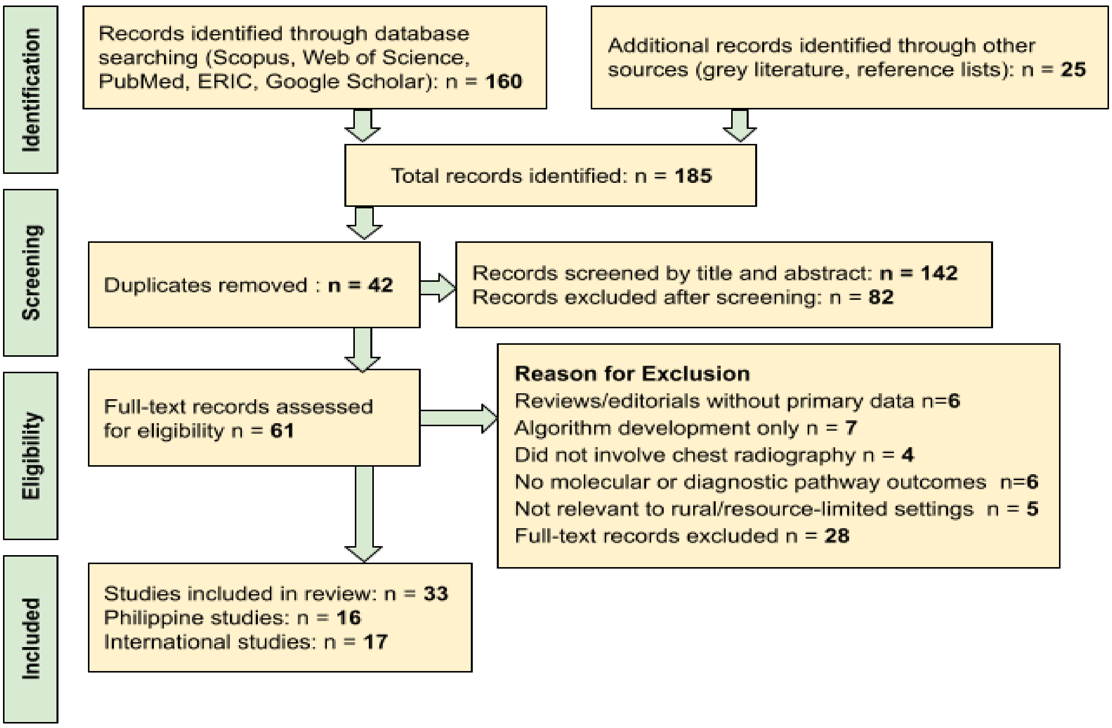

Figure 1. PRISMA flow diagram showing the study selection process for the systematic review on AI-assisted chest radiography as a triage tool for molecular laboratory testing in rural Philippine healthcare settings

RESULTS

Philippine Studies Diagnostic Accuracy and Performance Studies

Flores et al. (2025) conducted a prospective cohort study following STARD guidelines to evaluate the diagnostic performance of qXR version 3.0 compared with radiologist interpretations for tuberculosis (TB) screening among adults in Metro Manila, Philippines. Participants underwent chest radiography and Xpert MTB/RIF molecular testing as the reference standard. qXR 3.0 demonstrated 100% sensitivity and 72.7% specificity, meeting World Health Organization (WHO) screening benchmarks. Strong concordance between AI and

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radiologist interpretations was observed, suggesting that AI-assisted chest radiography may help address radiologist shortages and improve TB screening capacity in the Philippines.

Marquez et al. (2025) conducted a retrospective cross-sectional analysis across four Philippine regions evaluating AI-powered computer-aided detection (AI-CAD) integrated with chest X-ray (CXR) screening for active TB case finding. Using molecular World Health Organization–recommended rapid diagnostic (mWRD) tests as the reference standard, the AI-CAD system achieved very high pseudo-sensitivity (95.6%) but lower pseudo-specificity (28.1%). Receiver operating characteristic analysis yielded an area under the curve (AUC) of 0.820. Threshold analyses demonstrated important trade-offs between reducing molecular testing burden and avoiding missed TB cases, emphasizing the importance of context-specific calibration.

Nampewo et al. (2024) retrospectively compared AI-assisted CXR interpretation with conventional human-reader interpretation within the Philippine Business for Social Progress (PBSP) active case-finding program. The AI-assisted workflow demonstrated improved operational efficiency, with a lower number needed to screen (26.3 vs. 41.5) and substantially lower patient drop-out rates (16.6% vs. 43.1%) compared with human-reader interpretation. Faster AI-generated results also contributed to higher treatment initiation rates.

Philipsen et al. (2019) evaluated automated CXR interpretation within the DetecTB program in Palawan, Philippines. Automated software interpretations were compared with physician readings using Xpert MTB/RIF confirmation. The study demonstrated favorable sensitivity and specificity for AI-assisted interpretation and highlighted the incremental diagnostic yield of combining AI with physician review.

Implementation and Programmatic Studies

Stop TB Partnership (2024) implemented an intervention under the Introducing New Tools Project (iNTP) integrating ultra-portable digital chest X-ray systems, CAD4TB software, and Truenat molecular testing across geographically isolated and disadvantaged areas (GIDAs) in the Philippines. The intervention demonstrated the operational feasibility of combining AI-assisted radiography with portable molecular diagnostics for community-based TB screening and active case finding.

Lecciones et al. (2024) implemented active TB case finding in urban poor communities in Metro Manila using mobile vans equipped with AI-powered CAD chest X-ray systems integrated with primary healthcare services. Presumptive TB cases identified through symptoms or CAD-AI were referred for confirmatory molecular testing. The study highlighted the feasibility of integrating AI-assisted TB screening into broader primary healthcare delivery systems.

Dati (2025) described the implementation of AI-assisted ultra-portable chest X-ray systems in South Cotabato, Philippines, focusing on decentralized screening in rural and remote communities. The program emphasized rapid on-site screening, integration with local health systems, and improved access to TB services in underserved populations. Escosio (2026) described the deployment of an ultra-portable AI-powered X-ray system (REMEX KA6) in remote island communities in Batanes, Philippines. The battery-operated device enabled rapid point-of-care TB screening and reduced dependence on centralized hospital facilities. University Research Co. (2024) described a community-based TB screening program combining AI-assisted ultra-portable chest X-ray systems with Truenat mobile molecular testing in geographically isolated Philippine communities. The integrated workflow significantly reduced diagnostic turnaround time and improved accessibility to TB diagnostic services.

Japan International Cooperation Agency (JICA) (2023) implemented a pilot program with the Philippine Department of Health evaluating AI-assisted CAD chest X-ray screening in Muntinlupa City. The program demonstrated improved identification of presumptive TB cases and strengthened linkage to diagnostic follow-up and treatment.

Villanueva (2025) reported large-scale implementation of AI-assisted TB screening across 28 public hospitals and health centers in Luzon through a partnership between Siemens Healthineers and PBSP. AI-generated chest X-ray interpretations enabled rapid presumptive TB identification and improved diagnostic throughput in facilities with limited radiology workforce.

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Digital Health and Diagnostic Infrastructure Studies

Philippine Council for Health Research and Development (PCHRD) (2023) conducted qualitative descriptive analyses based on multi-stakeholder expert discussions regarding digital healthcare transformation in the Philippines. Key themes included digital infrastructure, workforce capacity, governance, telemedicine implementation, and integration of digital innovations into healthcare systems.

Alberto et al. (2022) examined the availability and accessibility of diagnostic services in the Philippines, identifying major regional disparities in infrastructure, workforce distribution, and healthcare financing. The study emphasized the importance of strengthening diagnostic systems and expanding access to imaging and laboratory technologies. Tan-Lim et al. (2025) developed Philippine guidance documents for the use of real-world evidence (RWE) in health technology assessment through systematic review and expert consultation. The study provided methodological guidance relevant to evaluating emerging technologies such as AI-assisted diagnostics.

Additional Philippine AI Imaging Studies

Baltazar et al. (2021) developed and evaluated deep learning models for COVID-19 pneumonia detection using chest X-rays in the Philippines. Multiple convolutional neural network architectures achieved strong diagnostic performance, demonstrating the broader applicability of AI-assisted radiographic interpretation within Philippine healthcare settings. Carnimeo et al. (2024) conducted a community-based implementation and feasibility study in Tondo, Manila using AI-assisted CAD software for active TB case finding. Threshold calibration strategies were applied to optimize resource utilization and confirmatory GeneXpert testing. The study demonstrated operational feasibility, acceptability, and linkage-to-treatment benefits in high-burden urban communities.

International Studies Diagnostic Accuracy and Validation Studies

Qin et al. (2019) conducted a retrospective multi-site diagnostic accuracy study in Nepal and Cameroon evaluating three AI systems (CAD4TB, qXR, and Lunit INSIGHT) against Xpert MTB/RIF confirmation. All systems demonstrated high diagnostic accuracy, with AUC values ranging from 0.92 to 0.94. AI-assisted triage reduced follow-on Xpert testing by up to 66% while maintaining sensitivity above 95%. Qin et al. (2021) evaluated five commercially available AI-CAD systems for TB triage in Bangladesh using Xpert confirmation as the reference standard. qXR and CAD4TB met WHO minimum triage criteria, achieving specificity above 72% at 90% sensitivity, while reducing the need for follow-up Xpert testing by more than 50%.

Biewer et al. (2024) assessed qXR versions 3.0 and 4.0 within a hospital-based FAST strategy in Peru. qXR v4 achieved high sensitivity (0.91–0.93) but lower specificity (~0.32–0.44), supporting its use as a highly sensitive triage tool while emphasizing the need for setting-specific threshold optimization. Jiang et al. (2025) evaluated AI-powered CAD as a triage tool for pulmonary TB in China using real-world data from county- and township-level healthcare facilities. AI-CAD identified 83.9% of confirmed TB cases compared with 25.6% detected by radiologists while reducing radiologist workload by 85.5%.

Nijiati et al. (2022) evaluated deep convolutional neural network models for active pulmonary TB detection using chest X-rays in China. The ResNet model demonstrated excellent performance with 96.73% accuracy, 95.50% sensitivity, 98.05% specificity, and an AUC of 0.9944. Chiu et al. (2025) evaluated a deep learning TB detection model using chest radiographs and PCR confirmation in Taiwan. The model achieved strong internal validation performance (AUC 0.915) and demonstrated potential as a triage tool for identifying patients requiring molecular testing.

Cost-Effectiveness and Modelling Studies

Raval et al. (2025) conducted a rapid health technology assessment in India evaluating AI-assisted CXR interpretation tools (qXR and Genki). AI-assisted interpretation substantially reduced cost per interpreted case compared with radiologist interpretation and demonstrated favorable incremental cost-effectiveness ratios, supporting the economic viability of AI-assisted TB screening. Codlin et al. (2024) modeled the impact of combining AI-assisted chest radiography with sputum pooling strategies across Bangladesh, Nigeria, Vietnam, and Zambia. The optimal strategy reduced Xpert test utilization by 50.8%–61.5%, potentially expanding molecular diagnostic coverage by up to 160%.

Mandal et al. (2026) used mathematical modelling to estimate the epidemiological impact of scaling up AI-enabled ultra-portable chest X-ray systems integrated with Xpert and Truenat testing across ten high-burden Asian countries. Community-based AI-assisted screening with molecular confirmation was projected to avert approximately 9.8 million TB cases and 1.9 million deaths over ten years.

Implementation and Operational Studies

Eneogu et al. (2024) evaluated the Wellness on Wheels (WoW) mobile TB screening model in Nigeria integrating digital chest radiography, CAD4TB, and GeneXpert testing. Iterative refinements improved screening efficiency, treatment initiation, and diagnostic yield, highlighting the feasibility of AI-assisted mobile screening. Yang et al. (2025) published a study protocol for a cluster randomized controlled trial in China evaluating CAD-assisted chest X-ray screening within primary healthcare settings. The study aims to assess diagnostic yield, diagnostic delay, and implementation feasibility.

Reviews and Methodological Studies

Hwang et al. (2024) conducted a narrative review and critical appraisal of AI-based CAD systems for TB detection using chest radiography. The review synthesized findings from real-world implementation and diagnostic studies, highlighting strong diagnostic performance while emphasizing economic, ethical, and policy considerations for scalability.

Other AI Radiology Studies Relevant to Diagnostic Workflow Optimization

Several studies outside tuberculosis (TB) screening have demonstrated the broader role of AI-assisted radiographic interpretation in improving diagnostic efficiency and workflow optimization. Ippolito et al. (2023) evaluated AI-assisted differentiation of COVID-19 pneumonia and bacterial pneumonia using chest X-rays, highlighting the potential of AI to support rapid and accurate diagnosis. Similarly, Májovský et al. (2025) demonstrated improved diagnostic accuracy among military physicians interpreting chest radiographs with AI assistance. In a real-world clinical setting, Kromrey et al. (2024) assessed concordance between AI software and radiologist diagnoses in chest radiography, showing substantial agreement between AI systems and human experts. Furthermore, Liu et al. (2026) reported improved reporting efficiency in AI-assisted chest CT interpretation using a quasi-experimental difference-in-differences design. In addition, Castilla et al. (2025) externally validated a deep learning chest radiograph triage system and demonstrated strong sensitivity and specificity for thoracic abnormality detection. Collectively, these studies support the broader applicability of AI-assisted imaging technologies in enhancing diagnostic workflows, improving efficiency, and addressing workforce limitations within healthcare systems.

DISCUSSIONS

The findings of this systematic review demonstrate that AI-assisted chest radiography has substantial potential to strengthen tuberculosis (TB) diagnostic pathways and improve access to molecular laboratory testing in rural and resource-limited healthcare settings in the Philippines. Across both Philippine and international studies, AI-powered computer-aided detection (AI-CAD) systems consistently demonstrated high sensitivity in identifying presumptive TB cases requiring confirmatory molecular testing. These findings support previous evidence that artificial intelligence can augment radiologic interpretation and improve screening efficiency in settings with limited radiology expertise (Hosny et al., 2018; Geric et al., 2023). In the Philippine context, studies by Flores et al. (2025) and Marquez et al. (2025) demonstrated that AI-assisted chest radiography met or exceeded World Health Organization (WHO) benchmarks for TB screening tools, suggesting that AI systems may function effectively as triage mechanisms for molecular diagnostics such as Xpert MTB/RIF and Truenat testing. The consistency of these findings across geographically diverse settings indicates that AI-assisted radiographic screening may offer a scalable approach for strengthening diagnostic capacity in underserved communities.

One of the most important findings of this review was the consistently high sensitivity reported among AI-assisted chest radiography systems. High sensitivity is particularly valuable in TB screening because missed diagnoses contribute to delayed treatment initiation, continued disease transmission, and worse clinical outcomes. Several international studies included in this review, including those by Qin et al. (2019), Qin et al. (2021), and Biewer et al. (2024), demonstrated that AI-CAD systems maintained sensitivities above 90% while substantially reducing the need for follow-up molecular testing. Similarly, Flores et al. (2025) reported 100% sensitivity for qXR version 3.0 in Philippine TB screening cohorts. These findings align with previous literature indicating that deep learning–based chest radiograph interpretation systems are particularly effective in identifying radiographic abnormalities suggestive of pulmonary TB (Rajpurkar et al., 2017; Hwang et al., 2024). From a public health perspective, maximizing sensitivity is especially critical in high-burden settings such as the Philippines, where underdiagnosis remains a major challenge in TB control programs.

Despite strong sensitivity, several studies reported lower specificity among AI-assisted screening systems, particularly when thresholds were optimized to maximize case detection. Marquez et al. (2025) observed high pseudo-sensitivity but substantially lower pseudo-specificity, while Biewer et al. (2024) similarly reported reduced specificity in hospital-based screening environments. This trade-off between sensitivity and specificity is expected in triage-oriented diagnostic systems because prioritizing sensitivity inevitably increases the number of false-positive referrals for confirmatory testing. Although lower specificity may increase molecular testing demand and healthcare costs, this approach may still be clinically acceptable in resource-constrained environments where the consequences of missed TB cases are severe. The findings therefore support recommendations from the WHO (2021) emphasizing the importance of context-specific threshold calibration and local validation of AI-assisted screening tools before implementation. Threshold optimization may allow healthcare systems to balance resource utilization with diagnostic performance according to local disease prevalence and laboratory capacity.

Another major finding of this review was the potential of AI-assisted chest radiography to improve diagnostic yield and optimize molecular testing pathways. Multiple studies demonstrated that AI-assisted triage reduced unnecessary molecular testing while preserving high case detection rates. Qin et al. (2019) reported that AI-assisted triage reduced Xpert MTB/RIF utilization by up to 66% while maintaining high sensitivity. Similarly, Codlin et al. (2024) showed that integrating AI-assisted radiography with sputum pooling strategies could reduce Xpert utilization by more than 50% while expanding diagnostic coverage. In the Philippines, Nampewo et al. (2024) found that AI-assisted workflows improved operational efficiency, reduced patient drop-out rates, and increased treatment initiation compared with conventional human-reader interpretation. These findings suggest that AI-assisted triage can contribute not only to improved diagnostic accuracy but also to more efficient allocation of limited molecular diagnostic resources. In rural healthcare systems where GeneXpert or Truenat machines may be scarce, optimizing laboratory utilization is essential for sustaining equitable diagnostic access.

The findings also highlight the important role of AI-assisted chest radiography in promoting health equity in rural and geographically isolated communities. Healthcare access in the Philippines remains uneven, with many rural regions lacking radiologists, imaging infrastructure, and accessible molecular diagnostic laboratories (Alberto et al., 2022; Panganiban et al., 2024). Several implementation studies included in this review demonstrated that portable AI-assisted chest X-ray systems enabled rapid point-of-care screening in geographically isolated and disadvantaged areas (GIDAs). Programs described by Stop TB Partnership (2024), University Research Co. (2024), Dati (2025), and Escosio (2026) demonstrated that ultra-portable digital radiography systems integrated with AI-CAD software and mobile molecular testing platforms could significantly reduce diagnostic delays in underserved communities. These findings support broader evidence that digital health technologies can help bridge healthcare disparities by decentralizing diagnostic services and reducing dependence on centralized hospital infrastructure (Frija et al., 2021; PCHRD, 2023).

Beyond improving healthcare access, AI-assisted radiographic triage may also help address workforce shortages in low-resource settings. The Philippines continues to experience maldistribution of healthcare professionals, including radiologists and laboratory personnel, particularly in rural provinces (Department of Health Philippines, 2023). AI-assisted interpretation systems can provide frontline healthcare workers with rapid decision-support tools capable of identifying presumptive TB cases in settings where specialist interpretation is unavailable. Jiang et al. (2025) demonstrated that AI-CAD systems substantially reduced radiologist workload while improving case detection rates compared with conventional radiologist interpretation alone. Similarly, Nampewo et al. (2024) reported improved screening efficiency and reduced delays with AI-assisted workflows in Philippine active case-finding programs. These findings support previous studies suggesting that AI may augment rather than replace healthcare professionals by improving workflow efficiency and allowing human expertise to be directed toward more complex diagnostic tasks (Topol, 2019; Gu et al., 2026).

The operational feasibility of AI-assisted chest radiography was another important theme identified across the included studies. Multiple Philippine implementation programs demonstrated successful integration of AI-assisted chest X-ray systems within community-based TB screening initiatives, mobile clinics, and primary healthcare services. Studies by Lecciones et al. (2024), JICA (2023), and Villanueva (2025) highlighted the adaptability of AI-assisted systems across diverse healthcare settings, including urban poor communities, rural municipalities, and public hospital networks. These implementation experiences suggest that AI-assisted radiographic triage may be integrated into existing TB control programs without requiring extensive infrastructure expansion. Furthermore, the growing availability of battery-operated ultra-portable X-ray systems may improve the sustainability of screening programs in remote areas with unreliable electricity and transportation infrastructure.

The broader implications of AI-assisted imaging technologies extend beyond TB screening alone. Several studies included in this review demonstrated the applicability of AI-assisted chest imaging for other respiratory and thoracic conditions, including COVID-19 pneumonia and general thoracic abnormality detection (Baltazar et al., 2021; Ippolito et al., 2023; Castilla et al., 2025). These findings suggest that investments in AI-assisted imaging infrastructure may provide broader health system benefits by strengthening radiologic diagnostic capacity across multiple disease categories. As digital health systems continue to evolve in the Philippines, integrating AI-assisted imaging technologies into national diagnostic programs may contribute to more resilient and efficient healthcare delivery systems.

Despite these promising findings, several important limitations within the available evidence must be acknowledged. Many included studies were retrospective or observational in design, limiting the ability to establish causal relationships between AI-assisted triage and improved clinical outcomes. Considerable heterogeneity also existed across studies in terms of AI software platforms, screening thresholds, study populations, and reference standards. Additionally, several implementation reports lacked standardized reporting of diagnostic accuracy metrics or long-term patient outcomes. Few studies directly evaluated cost-effectiveness, ethical considerations, data governance issues, or patient acceptability of AI-assisted diagnostic systems in rural settings. Furthermore, most evidence focused on tuberculosis screening, limiting generalizability to other diseases requiring molecular laboratory confirmation. These limitations highlight the need for prospective implementation trials, standardized reporting frameworks, and long-term health systems evaluations in low-resource settings.

This systematic review itself also has several limitations. The review included only English-language studies published between 2023 and 2026, which may have excluded relevant earlier or non-English literature. Additionally, some Philippine implementation studies originated from programmatic reports and organizational publications rather than peer-reviewed journals, potentially increasing the risk of publication bias. Nevertheless, including these reports was important because they provided valuable real-world implementation evidence relevant to rural healthcare delivery and diagnostic equity within the Philippine setting.

The findings of this systematic review suggest that AI-assisted chest radiography represents a promising strategy for strengthening molecular diagnostic triage pathways and improving equitable access to TB diagnostic services in rural Philippine communities. By combining high diagnostic sensitivity with operational scalability, AI-assisted radiographic screening may help optimize molecular testing utilization, reduce diagnostic delays, and address healthcare workforce shortages in underserved settings. However, successful large-scale implementation will require careful threshold calibration, infrastructure investment, workforce training, governance frameworks, and continued evaluation of clinical and economic outcomes. Future research should prioritize prospective real-world implementation studies, cost-effectiveness analyses, and equity-focused evaluations to better define the long-term role of AI-assisted diagnostics in Philippine healthcare systems.

CONCLUSION

This systematic review demonstrates that AI-assisted chest radiography is a promising triage tool for molecular tuberculosis (TB) testing in rural and resource-limited healthcare settings. The evidence indicates that AI-assisted chest radiography consistently achieves high sensitivity for identifying presumptive TB cases, improves diagnostic yield, optimizes the use of molecular diagnostic tests such as GeneXpert and Truenat, and enhances access to diagnostic services in underserved communities. The integration of portable AI-enabled chest X-ray systems with molecular testing platforms may help address diagnostic delays, healthcare workforce shortages, and inequities in healthcare access, particularly in geographically isolated areas of the Philippines. Despite these benefits, challenges related to specificity, infrastructure readiness, and implementation capacity remain. Future studies should incorporate meta-analytic approaches to generate pooled estimates of diagnostic accuracy, while prospective implementation studies and comprehensive cost-effectiveness analyses are needed to evaluate the long-term effectiveness, scalability, sustainability, and economic impact of AI-assisted chest radiography programs within the Philippine healthcare system.

LIMITATIONS

Several limitations should be considered when interpreting the findings of this systematic review. First, a quantitative meta-analysis was not performed because of substantial heterogeneity among the included studies with respect to AI platforms, diagnostic thresholds, study designs, healthcare settings, reference standards, and reported outcome measures. Consequently, pooled estimates of diagnostic accuracy could not be generated. Second, many of the included studies were retrospective, observational, or implementation-based in design, limiting the ability to establish causal relationships between AI-assisted chest radiography and improved clinical outcomes. Third, some evidence was derived from programmatic reports and grey literature, which may be subject to reporting bias and variability in methodological rigor. Additionally, differences in healthcare infrastructure, resource availability, and screening protocols across countries may limit the generalizability of findings to all rural Philippine settings. Finally, relatively few studies evaluated long-term outcomes, scalability, sustainability, or cost-effectiveness, highlighting important areas for future research.

RECOMMENDATIONS

Future research should focus on strengthening the evidence base for AI-assisted chest radiography as a triage tool for molecular tuberculosis testing. Studies employing meta-analytic techniques are needed to generate pooled estimates of diagnostic accuracy, including sensitivity, specificity, and area under the curve (AUC), thereby providing more robust evidence for clinical practice and health policy decision-making. Additional prospective implementation studies should be conducted in real-world healthcare settings, particularly in rural and geographically isolated areas of the Philippines, to evaluate the effectiveness, scalability, sustainability, and long-term impact of AI-assisted chest radiography programs. Furthermore, comprehensive cost-effectiveness analyses are necessary to determine whether AI-assisted screening offers long-term economic advantages over conventional diagnostic approaches through improved resource utilization, reduced unnecessary molecular testing, and earlier disease detection. Future investigations should also examine health equity outcomes, workforce training requirements, digital infrastructure readiness, and governance frameworks to support the safe, effective, and equitable integration of AI-assisted diagnostic technologies into national tuberculosis control programs.

REFERENCES

1. Alberto, N. R. I., Alberto, I. R. I., Eala, M. A. B., Dee, E. C., & Cañal, J. P. A. (2022). Availability of essential diagnostics in the Philippines. The Lancet Regional Health – Western Pacific, 19, 100375. https://doi.org/10.1016/j.lanwpc.2021.100375
2. Baltazar, L. R., Manzanillo, M. G., Gaudillo, J., Viray, E. D., Domingo, M., Tiangco, B., & Albia, J. (2021). Artificial intelligence on COVID-19 pneumonia detection using chest X-ray images. PLOS ONE, 16(10), e0257884. https://doi.org/10.1371/journal.pone.0257884
3. Biewer, A. M., Tzelios, C., Tintaya, K., Roman, B., Hurwitz, S., Yuen, C. M., Mitnick, C. D., Nardell, E., Lecca, L., Tierney, D. B., & Nathavitharana, R. R. (2024). Accuracy of digital chest X-ray analysis

with artificial intelligence software as a triage and screening tool in hospitalized patients being evaluated for tuberculosis in Lima, Peru. PLOS Global Public Health, 4(2), e0002031. https://doi.org/10.1371/journal.pgph.0002031

4. Carnimeo, V., et al. (2024). Enhancing tuberculosis diagnosis with AI: Insights from a study in Manila, Philippines. Epicentre / Médecins Sans Frontières. https://epicentre.msf.org/en/news/enhancing-tuberculosis-diagnosis-ai-insights-study-manila-philippines
5. Castilla, A. C., D'Amorim, I. de P., Wanderley, M. F. B., Esmeraldo, M. A., Yoshida, A. R., Eigier, A. M., & Sawamura, M. V. Y. (2025). External validation of an artificial intelligence triaging system for chest X-rays: A retrospective independent clinical study. Diagnostics, 15(22), 2899. https://doi.org/10.3390/diagnostics15222899
6. Chiu, W.-C., Chang, S.-Y., Lin, C., Chen, T.-W., & Fang, W.-H. (2025). Integrating AI with PCR for Tuberculosis Diagnosis: Evaluating a Deep Learning Model for Chest X-Rays. Bioengineering, 12(12), 1377. https://doi.org/10.3390/bioengineering12121377
7. Codlin, A. J., Vo, L. N. Q., Garg, T., Banu, S., Ahmed, S., John, S., Abdulkarim, S., Muyoyeta, M., Sanjase, N., Wingfield, T., Iem, V., Squire, B., & Creswell, J. (2024). Expanding molecular diagnostic coverage for tuberculosis by combining computer-aided chest radiography and sputum specimen pooling: A modeling study from four high-burden countries. BMC Global and Public Health, 2, 52. https://doi.org/10.1186/s44263-024-00081-2
8. Cole, B., Nilsen, D. M., Will, L., Etkind, S. C., Burgos, M., & Chorba, T. (2020). Essential components of a public health tuberculosis prevention, control, and elimination program: Recommendations of the Advisory Council for the Elimination of Tuberculosis and the National Tuberculosis Controllers Association. MMWR Recommendations and Reports, 69(RR-7), 1–27. https://doi.org/10.15585/mmwr.rr6907a1
9. Dati, M. (2025). AI-driven TB detection now in 8 areas of South Cotabato. Province of South Cotabato Official Website. https://southcotabato.gov.ph/ai-driven-tb-detection-now-in-8-areas-of-south-cotabato/
10. Department of Health Philippines. (2023). Philippine health system review. Manila: Department of Health.
11. Eneogu, R. A., Mitchell, E. M. H., Ogbudebe, C., Aboki, D., Anyebe, V., Dimkpa, C. B., Egbule, D., Nsa, B., van der Grinten, E., Soyinka, F. O., Abdur-Razzaq, H., Useni, S., Lawanson, A., et al., & Gidado, M. (2024). Iterative evaluation of mobile computer-assisted digital chest x-ray screening for TB improves efficiency, yield, and outcomes in Nigeria. PLOS Global Public Health. https://doi.org/10.1371/journal.pgph.0002018
12. Eric Topol. (2019). Deep medicine: How artificial intelligence can make healthcare human again. Retrieved March 13, 2026, from https://drerictopol.com/portfolio/deep-medicine/
13. Escosio, J. (2026). PCSO brings to Batanes ultra-portable AI X-ray technology tested by NASA. INQUIRER.net. https://newsinfo.inquirer.net/2199965/pcso-brings-to-batanes-ultra-portable-ai-x-ray-technology-tested-by-nasa
14. Essa, M. E. A. (2025). Diagnostic accuracy of AI in chest radiography for pneumonia and lung cancer: A meta-analysis. European Journal of Radiology Open, 15, 100701. https://doi.org/10.1016/j.ejro.2025.100701
15. Esteva, A., Robicquet, A., Ramsundar, B., et al. (2019). A guide to deep learning in healthcare. Nature Medicine, 25(1), 24–29. https://doi.org/10.1038/s41591-018-0316-z
16. Feng, G., Jiang, H., & Chen, Y. (2025). Efficacy of Xpert MTB/RIF assay in detecting Mycobacterium tuberculosis in samples with different results by smear and culture in a coastal city with high incidence of tuberculosis. BMC Infectious Diseases, 25, 55. https://doi.org/10.1186/s12879-025-10446-z
17. Flores, G. P., Tamayo, R. L. J., Leong, R. N. F., Biglaen, C. S. M., Uy, K. N. T., Maglente, R. R. O., Nuguid, M. J. M., & Alacapa, J. V. (2025). Diagnostic performance of a computer-aided system for tuberculosis screening in two Philippine cities. Acta Medica Philippina, 59(2), 33–40. https://doi.org/10.47895/amp.vi0.8950
18. Frija, G., Blažić, I., Frush, D. P., Hierath, M., Kawooya, M., Donoso-Bach, L., & Brkljačić, B. (2021). How to improve access to medical imaging in low- and middle-income countries? eClinicalMedicine, 38, 101034. https://doi.org/10.1016/j.eclinm.2021.101034
19. Geric, C., Qin, Z. Z., Denkinger, C. M., Kik, S. V., Marais, B., Anjos, A., David, P. M., Ahmad Khan, F., & Trajman, A. (2023). The rise of artificial intelligence reading of chest X-rays for enhanced TB

diagnosis and elimination. International Journal of Tuberculosis and Lung Disease, 27(5), 367–372. https://doi.org/10.5588/ijtld.22.0687

20. Gu, Z., Dogra, S., Siriruchatanon, M., Kneifati-Hayek, J., & Kang, S. K. (2026). Radiology workflow assistance with artificial intelligence: Establishing the link to outcomes. Journal of the American College of Radiology, 23(3), 389–398. https://doi.org/10.1016/j.jacr.2025.10.018
21. Hanna, M. G., Pantanowitz, L., Dash, R., Harrison, J. H., Deebajah, M., Pantanowitz, J., & Rashidi, H. H. (2025). Future of artificial intelligence—Machine learning trends in pathology and medicine. Modern Pathology, 38(4), 100705. https://doi.org/10.1016/j.modpat.2025.100705
22. Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. W. L. (2018). Artificial intelligence in radiology. Nature Reviews Cancer, 18(8), 500–510. https://doi.org/10.1038/s41568-018-0016-5
23. Hwang, E. J., Jeong, W. G., David, P. M., Arentz, M., Ruhwald, M., & Yoon, S. H. (2024). AI for Detection of Tuberculosis: Implications for Global Health. Radiology: Artificial Intelligence, 6(2), e230327. https://doi.org/10.1148/ryai.230327
24. Ippolito, D., Maino, C., Gandola, D., Franco, P. N., Miron, R., Barbu, V., Bologna, M., Corso, R., & Breaban, M. E. (2023). Artificial Intelligence Applied to Chest X-ray: A Reliable Tool to Assess the Differential Diagnosis of Lung Pneumonia in the Emergency Department. Diseases, 11(4), 171. https://doi.org/10.3390/diseases11040171
25. Japan International Cooperation Agency (JICA). (2023). JICA-DOH cooperation takes TB diagnosis in PH to new heights using AI tech. https://www.jica.go.jp/english/overseas/philippine/information/press/2023/1516623_16864.html
26. Jiang, W., Zhang, H., Li, Z., Jiang, X., Shao, J., Yang, X., Xiong, J., Zhou, P., Zhang, H., Wang, H., Yu, J., Su, X., Wang, Y., Liu, J., & Li, Z. (2025). AI-powered chest X-ray for diagnosing pulmonary tuberculosis in county and township health care facilities in Yichang: Retrospective, real-world study. Journal of Medical Internet Research, 27, e83041. https://doi.org/10.2196/83041
27. Kelly, C.J., Karthikesalingam, A., Suleyman, M., Corrado, G. and King, D. (2019) Key Challenges for Delivering Clinical Impact with Artificial Intelligence. BMC Medicine, 17, Article No. 195.https://doi.org/10.1186/s12916-019-1426-2
28. Kromrey, M.-L., Steiner, L., Schön, F., Gamain, J., Roller, C., & Malsch, C. (2024). Navigating the Spectrum: Assessing the Concordance of ML-Based AI Findings with Radiology in Chest X-Rays in Clinical Settings. Healthcare, 12(22), 2225. https://doi.org/10.3390/healthcare12222225
29. Lecciones, J., Ubalde, J. P., Santiago, M. R., Guirgis, S., & Stevens, L. (2024). Integrating TB screening with other primary healthcare services in urban poor communities in the Philippines. Union Conference on Lung Health. https://www.radisentech.com/publication/integrating-tb-screening-with-other-primary-healthcare-services-in-urban-poor-communities-in-the-philippines/
30. Liu, W., Wu, Y., Yu, W., Bittle, M. J., Zheng, Z., & Kharrazi, H. (2026). Measuring the Impact of AI on Report-Drafting Efficiency in Chest Computed Tomography Interpretation: Retrospective Analysis. Journal of Medical Internet Research, 28, e77967. https://doi.org/10.2196/77967
31. Macpherson, L., Kik, S. V., Quartagno, M., Lakay, F., Jaftha, M., Yende, N., Galant, S., Aziz, S., Daroowala, R., Court, R., Taliep, A., Serole, K., Goliath, R. T., Davies, N. O., Jackson, A., Douglass, E., Sossen, B., Mukasa, S., Thienemann, F., Song, T., Ruhwald, M., Wilkinson, R. J., Coussens, A. K., & Esmail, H., for the Imaging of TB Household Contacts Group. (2025). Diagnostic accuracy of chest X-ray computer-aided detection software for detection of prevalent and incident tuberculosis in household contacts. Clinical Infectious Diseases, 80(3), 626–636. https://doi.org/10.1093/cid/ciae528
32. Májovský, M., Sedlák, V., Komarc, M., Henlín, T., Černý, M., Májovský, P., Tůma, T., Šustek, P., Široká, L., Šolc, M., Miklas, L., Kolouch, J., Svoboda, N., Páleník, J., Brixi, J., Gottvald, T., Šindelář, L., Kašper, Š., Chomič, J., Kuliha, O., Svoboda, P., Netuka, D., & Masopust, V. (2025). Artificial intelligence-assisted chest radiograph interpretation in Role 2 military field hospital settings: a controlled experimental study. Trauma Surgery & Acute Care Open, 10(4), e001700. https://doi.org/10.1136/tsaco-2024-001700
33. Mandal, S., Rade, K., Singh, A., Nair, S. A., & Sahu, S. (2026). Impact and cost of scaling up TB screening and diagnostics in Asia’s ten high-burden countries: A modelling analysis. medRxiv. https://doi.org/10.64898/2026.04.16.26351072

34. Marquez, N., Carpio, E. J., Santiago, M. R., Calderon, J., Orillaza-Chi, R., Salanap, S. S., & Stevens, L. (2025). Performance of chest X-ray with computer-aided detection powered by deep learning-based artificial intelligence for tuberculosis presumptive identification during case finding in the Philippines. BMC Global and Public Health, 3(1), 74. https://doi.org/10.1186/s44263-025-00198-y
35. Melford, C. M., & O'Brien-Melford, M. A. P. (2026). Artificial Intelligence Applications in Clinical Laboratory Diagnostics: A Systematic Review of Diagnostic Accuracy, Workflow Efficiency, and Clinical Utility. International Journal of Research and Scientific Innovation (IJRSI), 13(4), 2825–2833. https://doi.org/10.51244/IJRSI.2026.1304000242
36. Nampewo, I., Ariana, P., Vijayan, S., & Holthof, B. (2024). Benefits of artificial intelligence versus human-reader in chest X-ray screening for tuberculosis in the Philippines. International Journal of Health Sciences and Research, 14(2). https://doi.org/10.52403/ijhsr.20240237
37. Nijiati, M., Ma, J., Hu, C., Tuersun, A., Abulizi, A., Kelimu, A., Zhang, D., Li, G., & Zou, X. (2022). Artificial Intelligence Assisting the Early Detection of Active Pulmonary Tuberculosis From Chest X-Rays: A Population-Based Study. Frontiers in Molecular Biosciences, 9. https://doi.org/10.3389/fmolb.2022.874475
38. Panganiban, J. M. S., Loreche, A. M., De Mesa, R. Y. H., Camiling-Alfonso, R., Fabian, N. M. C., & Dans, L. F. (2024). Promoting equitable and patient-centred care: An analysis of patient satisfaction in urban, rural and remote primary care sites in the Philippines. BMJ Open Quality, 13, e002483. https://doi.org/10.1136/bmjoq-2023-002483
39. Pesapane, F., Codari, M., & Sardanelli, F. (2018). Artificial intelligence in medical imaging: Threat or opportunity? Radiologists again at the forefront of innovation in medicine. European Radiology Experimental, 2, 35. https://doi.org/10.1186/s41747-018-0061-6
40. Philippine Council for Health Research and Development (PCHRD). (2023). What the future of digital healthcare would look like in the Philippines. https://www.pchrd.dost.gov.ph/news_and_updates/what-the-future-of-digital-healthcare-would-look-like-in-the-philippines/
41. Philipsen, R. H. H. M., Sánchez, C. I., Melendez, J., Lew, W. J., & van Ginneken, B. (2019). Automated chest X-ray reading for tuberculosis in the Philippines to improve case detection: A cohort study. International Journal of Tuberculosis and Lung Disease, 23(7), 805–810. https://doi.org/10.5588/ijtld.18.0004
42. Qin, Z. Z., Ahmed, S., Sarker, M. S., Paul, K., Adel, A. S. S., Naheyan, T., Barrett, R., Banu, S., & Creswell, J. (2021). Tuberculosis detection from chest x-rays for triaging in a high tuberculosis-burden setting: An evaluation of five artificial intelligence algorithms. The Lancet Digital Health, 3(9), e543–e554. https://doi.org/10.1016/s2589-7500(21)00116-3
43. Qin, Z. Z., Sander, M. S., Rai, B., Titahong, C. N., Sudrungrot, S., Laah, S. N., Adhikari, L. M., Carter, E. J., Puri, L., Codlin, A. J., & Creswell, J. (2019). Using artificial intelligence to read chest radiographs for tuberculosis detection: A multi-site evaluation of the diagnostic accuracy of three deep learning systems. Scientific Reports, 9, 15000. https://doi.org/10.1038/s41598-019-51503-3
44. Rajpurkar, P., Irvin, J., Zhu, K., et al. (2017). CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. arXiv preprint, arXiv:1711.05225.
45. Raval, D., Parmar, D., Saha, S., Sarkar, R., Wadhwa, M., Pandya, A., Shah, H., & Rajsekar, K. (2025). Cost-effectiveness analysis of AI-assisted chest X-ray interpretation tools for TB screening: a rapid HTA. Frontiers in Digital Health, 7. https://doi.org/10.3389/fdgth.2025.1629127
46. Stop TB Partnership. (2024). Revolutionizing TB screening and testing: How ultra-portable digital X-ray with artificial intelligence-powered detection software together with on-site rapid molecular testing are reaching people across the Philippines (iNTP case study). https://www.stoptb.org/sites/default/files/imported/document/philippines_x-ray-cad_and_truenat_case_study_intp_mar24.pdf
47. Strubchevska, O., Kozyk, M., Kozyk, A., & Strubchevska, K. (2024). The role of artificial intelligence in diagnostic radiology. Cureus, 16(10), e72173. https://doi.org/10.7759/cureus.72173
48. Tan-Lim, C. S. C., Cabaluna, I. T. G., Infantado-Alejandro, M. A. J., Imbag, M. D. S., Lopez, L. F. L., Esteban-Ipac, N. A. R., Macalalad-Josue, A. A., Bayona, H. H. G., Burog, A. I. L. D., Cochon, K. L., & Alejandria, M. M. (2025). Development of the Philippine guidance document for the use of real-world evidence for clinical assessment of health technologies. International Journal of Technology Assessment in Health Care, 41(1), e72. https://doi.org/10.1017/S0266462325100512

49. University Research Co. (2024). AI-assisted ultraportable X-ray screening and Truenat testing extend the reach of TB diagnosis. https://www.urc-chs.com/news/ai-assisted-ultraportable-x-ray-screening-and-truenat-testing-extend-the-reach-of-tb-diagnosis/
50. Villanueva, G. (2025). Luzon hospitals, centers get help from TB-detecting AI. Philippine Daily Inquirer.https://newsinfo.inquirer.net/2045833/luzon-hospitals-centers-get-help-from-tb-detecting-ai
51. World Health Organization. (2018). The Philippines: Health system review (Health Systems in Transition, Vol. 8, No. 2). European Union. https://iris.who.int/server/api/core/bitstreams/d3ecbe57-f53f-4f89-992a-3c742ad1f57a/content
52. World Health Organization. (2021, March 22). WHO consolidated guidelines on tuberculosis: Module 2: Screening: Systematic screening for tuberculosis disease. https://www.who.int/publications/i/item/9789240022676
53. World Health Organization. (2026, March 24). Tuberculosis. https://www.who.int/news-room/fact-sheets/detail/tuberculosis
54. Yacat, N. A. (2024, December 11). Olongapo City receives AI-enabled, handy chest X-ray machine for the indigenous, unreached. Catholic Health Services, Inc. https://www.chsi.ph/olongapo-city-receives-ai-enabled-handy-chest-x-ray-machinefor-the-indigenous-unreached/
55. Yang, X., Zhang, H., Jiang, W., Xin, Y., Dai, Z., Li, Z., Xiong, J., Sun, R., Shao, J., Yu, J., Wang, Y., Su, X., Liu, J., & Li, Z. (2025). Effectiveness of computer-aided detection chest X-ray screening for improving tuberculosis diagnostic yield in Chinese primary healthcare settings: Study protocol for a prospective cluster randomised controlled trial. BMJ Open, 16(2). https://doi.org/10.1136/bmjopen-2025-112124

Table 1. Summary of Studies Included in the Systematic Review

Study Type	**Number of Studies (n)**	**Examples of Outcomes Reported**
Diagnostic Accuracy and Validation Studies	12	Sensitivity, specificity, AUC, diagnostic performance
Implementation and Operational Studies	10	Feasibility, workflow integration, treatment linkage, screening efficiency
Cost-Effectiveness and Modelling Studies	3	Molecular test reduction, economic impact, projected TB case reduction
Digital Health and Infrastructure Studies	3	Healthcare access, digital integration, workforce and infrastructure gaps
Review and Methodological Studies	2	AI implementation challenges, policy considerations
Other AI Imaging Workflow Studies	3	Reporting efficiency, workflow optimization, radiologist concordance
Total	**33**	

Table 2. Types of Studies Included in the Review

Characteristic	**Findings**
Main Disease Focus	Tuberculosis (TB)
Imaging Modality	Chest radiography / chest X-ray

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Common AI Systems Evaluated	qXR, CAD4TB, Lunit INSIGHT
Common Molecular Tests Used	Xpert MTB/RIF, GeneXpert, PCR, Truenat
Common Study Settings	Rural communities, public hospitals, mobile clinics, urban poor communities
Major Outcomes Evaluated	Diagnostic accuracy, diagnostic yield, workflow efficiency, health equity, implementation feasibility

Table 3. Summary and Classification of Studies Included in the Systematic Review According to Study Category, Authors, and Main Research Focus

Category of Studies	**Authors and Year**	**Main Focus**
Philippine diagnostic accuracy and performance studies	Flores et al. (2025); Marquez et al. (2025); Nampewo et al. (2024); Philipsen et al. (2019)	Diagnostic performance of AI-assisted chest radiography for TB screening and molecular testing triage
Philippine implementation and programmatic studies	Stop TB Partnership (2024); Lecciones et al. (2024); Dati (2025); Escosio (2026); University Research Co. (2024); JICA (2023); Villanueva (2025)	Operational feasibility, mobile screening, community-based TB detection, rural healthcare access
Philippine digital health and infrastructure studies	PCHRD (2023); Alberto et al. (2022); Tan-Lim et al. (2025)	Diagnostic infrastructure, digital health integration, healthcare accessibility
Additional Philippine AI imaging studies	Baltazar et al. (2021); Carnimeo et al. (2024)	AI-assisted chest imaging applications and workflow optimization
International diagnostic accuracy and validation studies	Qin et al. (2019); Qin et al. (2021); Biewer et al. (2024); Jiang et al. (2025); Nijiati et al. (2022); Chiu et al. (2025)	Sensitivity, specificity, AUC, AI-CAD validation for TB triage
International cost-effectiveness and modelling studies	Raval et al. (2025); Codlin et al. (2024); Mandal et al. (2026)	Resource optimization, molecular testing reduction, epidemiological impact
International implementation and operational studies	Eneogu et al. (2024); Yang et al. (2025)	Mobile AI-assisted screening and implementation feasibility
Reviews and methodological studies	Hwang et al. (2024)	AI-assisted TB detection and policy implications
Other AI radiology workflow studies	Ippolito et al. (2023); Májovský et al. (2025); Kromrey et al. (2024); Liu et al. (2026); Castilla et al. (2025)	Diagnostic workflow optimization, reporting efficiency, radiologist concordance
Total Studies Synthesized	**33 studies**	AI-assisted chest radiography and molecular diagnostic triage