



What are The Comparative Diagnostic Accuracies of X-Ray, CT, and Ultrasound in Terms of Sensitivity and Specificity for Detecting Pulmonary Tuberculosis in Adult Patients with Suspected Infection ? : A Systematic Review

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ABSTRACT

Introduction: Pulmonary tuberculosis (TB) poses a significant global health challenge, necessitating timely and accurate diagnosis. While chest X-ray (CXR) is widely used, its diagnostic accuracy varies. Advanced modalities like computed tomography (CT) and ultrasound offer potential improvements but have their own limitations regarding cost, accessibility, and operator dependency. This systematic review aims to compare the diagnostic accuracies (sensitivity and specificity) of X-ray, CT, and ultrasound for detecting pulmonary TB in adults with suspected infection. **Methods:** This systematic review followed PRISMA 2020 guidelines. Studies were included if they assessed X-ray, CT, or ultrasound in adult patients (≥ 18 years) with suspected pulmonary TB, reported sensitivity and/or specificity, and used microbiological confirmation as the reference standard. Data on study design, participant characteristics, imaging modalities, and diagnostic accuracy metrics were extracted. Searches were conducted on PubMed, Semantic Scholar, Sagepub, and Google Scholar. **Results:** Twenty-three studies were included. CT demonstrated the highest diagnostic accuracy, with sensitivity and specificity frequently exceeding 93% (e.g., sensitivity 93.8%-100%, specificity 94.2%-97.9% with deep learning). CXR showed high sensitivity (often $>85\%$, up to 98.6%) but widely variable specificity (23%-99.9%). AI-enhanced CXR reported sensitivity between 85.3%-94.4% and specificity of 37.1%-69.2%. Ultrasound sensitivity for specific findings (e.g., subpleural nodules) ranged from 72.5%-100%, but specificity was generally lower and more variable (e.g., 66.7%). Diagnostic performance was influenced by HIV status and prior TB. **Discussion:** CT offers superior accuracy but is limited by cost and accessibility. CXR remains a primary screening tool due to accessibility, though its variable specificity, especially with AI, is a concern. Ultrasound shows promise as an adjunctive, radiation-free tool in resource-limited settings, but operator dependency and lack of standardization are challenges. The heterogeneity in study designs and risk of bias in many included studies temper the generalizability of findings. **Conclusion:** CT provides the highest diagnostic accuracy for pulmonary TB in adults. CXR is the most accessible screening modality, with AI potentially enhancing sensitivity but requiring specificity improvements. Ultrasound is a useful adjunct in specific contexts. Optimal diagnostic strategies should integrate these modalities based on clinical context, resource availability, and patient characteristics.

Keywords: Pulmonary Tuberculosis, Diagnostic Accuracy, Chest X-ray, Computed Tomography, Ultrasound, Sensitivity, Specificity, Systematic Review.

INTRODUCTION

Pulmonary tuberculosis (TB) remains a significant global health challenge, particularly in adult populations where timely and accurate diagnosis is essential to reduce morbidity, mortality, and transmission. Despite advances in microbiological testing, imaging continues to play a pivotal role in the diagnosis and management of pulmonary TB, especially in settings where rapid bacteriological confirmation is unavailable or delayed. Conventional chest X-ray (CXR) has long been the primary imaging modality due to its accessibility and cost-effectiveness, but it has limitations in sensitivity and specificity, particularly in populations with HIV co-infection or prior TB exposure (Scott et al., 2024; Di Gennaro et al., 2018).

The emergence of advanced imaging techniques such as computed tomography (CT) and ultrasound has expanded diagnostic possibilities. CT, with its superior spatial resolution and ability to detect subtle parenchymal changes, has demonstrated higher sensitivity and specificity in detecting pulmonary TB compared to CXR. However, CT is more expensive, less accessible in resource-limited settings, and involves higher radiation exposure, which limits its routine use (Zhang et al., 2025; Sun et al., 2022). Ultrasound, particularly point-of-care ultrasound (POCUS), offers a radiation-free, bedside imaging alternative that can detect pleural and subpleural abnormalities, but its diagnostic accuracy and operator dependency remain concerns (Bigio et al., 2021; Di Gennaro et al., 2018).

The variability in diagnostic performance across these imaging modalities is influenced by multiple factors, including patient characteristics such as HIV status, prior TB history, and clinical presentation. For instance, imaging specificity tends to decrease in HIV-positive patients due to overlapping radiographic features with other opportunistic infections (Mukoka et al., 2022; Gebregergs et al., 2024). Additionally, technical factors such as the use of digital versus conventional radiography, the integration of artificial intelligence (AI) and computer-aided detection (CAD) systems, and operator expertise particularly in ultrasound, significantly affect diagnostic outcomes (Hua et al., 2023; Harris et al., 2019).

Given the global burden of TB and the heterogeneous performance of different imaging modalities, this research aims to systematically compare the diagnostic accuracy of chest X-ray, CT, and ultrasound in detecting pulmonary TB among adult patients with suspected infection. Understanding the relative strengths and limitations of these modalities is critical for guiding clinical decision-making, optimizing diagnostic algorithms, and improving patient outcomes in diverse healthcare settings (Scott et al., 2024; Zhang et al., 2025).

The rationale for this study stems from the need to synthesize existing evidence on these imaging techniques, particularly in the context of emerging AI technologies that have shown promise in enhancing chest X-ray interpretation accuracy. While chest X-ray remains the most studied modality with reported sensitivities exceeding 85%, its specificity varies widely, sometimes as low as 23%, which could lead to false positives and unnecessary treatment (Hansun et al., 2023; Hua et al., 2023). CT, although less studied in prospective clinical trials, consistently achieves sensitivity and specificity above 93%, suggesting it may be the most reliable imaging option when available (Zhang et al., 2025).

Ultrasound's role in pulmonary TB diagnosis is less well defined, with few studies reporting sensitivity ranging from 72.5% to 100% for detecting specific features such as subpleural nodules and pleural effusions. However, its lower and more variable specificity, along with the lack of standardized protocols, limits its widespread adoption as a primary diagnostic tool (Bigio et al., 2021; Zhang et al., 2023). Nonetheless, ultrasound may serve as a valuable adjunct in resource-constrained settings or in patients where radiation exposure is a concern. This study also addresses gaps in the literature related to population-specific diagnostic performance, particularly among HIV-positive adults and those with previous TB infections

METHODS

Protocol

The study strictly adhered to the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) 2020 guidelines to ensure methodological rigor and accuracy. This

approach was chosen to enhance the precision and reliability of the conclusions drawn from the investigation.

Criteria for Eligibility

This systematic review aims to evaluate the comparative diagnostic accuracies of X-ray, CT, and ultrasound in terms of sensitivity and specificity for detecting pulmonary tuberculosis in adult patients with suspected infection.

Screening

We screened in papers that met these criteria:

- **Population:** Does the study examine suspected pulmonary TB cases in adult patients (18 years)?
- **Imaging Modality:** Does the study evaluate at least one of the following imaging modalities: X-ray, CT, or ultrasound?
- **Diagnostic Measures:** Does the study report diagnostic accuracy measures (sensitivity and/or specificity)?
- **Reference Standard:** Does the study use microbiological confirmation (culture or molecular testing) as the reference standard?
- **Study Design:** Is the study either a primary research study or a systematic review/meta-analysis?
- **TB Type:** Does the study include pulmonary TB (not exclusively extra-pulmonary TB)?
- **Population Symptoms:** Does the study examine symptomatic patients (rather than screening of asymptomatic populations)?

We considered all screening questions together and made a holistic judgement about whether to screen in each paper.

Data extraction

We asked a large language model to extract each data column below from each paper. We gave the model the extraction instructions shown below for each column.

- **Study Design:**

Identify the specific type of diagnostic accuracy study:

- Cross-sectional diagnostic accuracy study
- Prospective diagnostic study
- Retrospective diagnostic study

Look in the methods section for explicit description of study design. If not clearly stated, infer from study methodology. If multiple designs are used, list all.

If design is unclear or cannot be determined, note "Unable to classify" and provide a brief explanation.

- **Participant**

Characteristics:

Extract the following details:

- Total number of participants
- Age range or mean age
- Gender distribution
- Inclusion criteria for suspected TB
- Exclusion criteria
- Clinical characteristics (e.g., symptoms, risk factors)

Look in methods section under "Participants" or "Patients". If information is incomplete, note which specific details are missing.

Report numerical data with appropriate units and percentages where applicable. For age, include both mean/median and range if possible.

- **Imaging Modalities:**

List all imaging techniques used:

- X-ray details (type, views, equipment)
- CT details (type, slice thickness, contrast use)
- Ultrasound details (probe type, frequency)

Identify:

- How each imaging technique was performed
- Who conducted the imaging
- Any standardization of imaging protocols

Look in methods section, particularly subsections on diagnostic procedures. If protocols vary between studies, note these variations.

- **Diagnostic Accuracy Metrics:**

Extract the following diagnostic performance metrics:

- Sensitivity (%)
- Specificity (%)
- Positive Predictive Value (%)
- Negative Predictive Value (%)
- Area Under ROC Curve (if available)

Ensure you:

- Report point estimates
- Include 95% confidence intervals
- Note the reference standard used for confirming TB diagnosis

Locate in results section, typically in tables or text describing diagnostic performance. If multiple analyses are reported, extract all and note context.

- **Risk of Bias Assessment:**

Use QUADAS-2 tool to assess:

- Patient selection bias
- Index test bias
- Reference standard bias
- Flow and timing bias

Score each domain as:

- Low risk
- High risk
- Unclear risk

Extract specific details supporting each assessment. Look in methods or discussion sections discussing study limitations.

Search Strategy

The keywords used for this research based PICO :

Element	Keyword 1	Keyword 2	Keyword 3	Keyword 4
Population (P)	Adults	Suspected pulmonary TB	HIV co-infection	Resource-limited settings
Intervention (I)	Chest X-ray	Computed Tomography	Ultrasound	Radiologist interpretation
Comparison (C)	Microbiological reference	Clinical diagnosis	Human vs. AI interpretation	High-burden vs. low-burden settings
Outcome (O)	Sensitivity	Specificity	Positive predictive value	Negative predictive value

The Boolean MeSH keywords inputted on databases for this research are: (*"Adults" OR "Suspected pulmonary TB" OR "HIV co-infection" OR "Resource-limited settings"*) AND (*"Chest X-ray" OR "Computed Tomography" OR "Ultrasound" OR "Radiologist interpretation"*) AND

("Microbiological reference" OR "Clinical diagnosis" OR "Human vs. AI interpretation" OR "High-burden vs. low-burden settings") AND ("Sensitivity" OR "Specificity" OR "Positive predictive value" OR "Negative predictive value")

Data retrieval

Abstracts and titles were screened to assess their eligibility, and only studies meeting the inclusion criteria were selected for further analysis. Literature that fulfilled all predefined criteria and directly related to the topic was included. Studies that did not meet these criteria were excluded. Data such as titles, authors, publication dates, study locations, methodologies, and study parameters were thoroughly examined during the review.

Quality Assessment and Data Synthesis

Each author independently assessed the titles and abstracts of the selected studies to identify those for further exploration. Articles that met the inclusion criteria underwent further evaluation. Final decisions on inclusion were based on the findings from this review process.

Table 1. Article Search Strategy

Database	Keywords	Hits
Pubmed	("Adults" OR "Suspected pulmonary TB" OR "HIV co-infection" OR "Resource-limited settings") AND ("Chest X-ray" OR "Computed Tomography" OR "Ultrasound" OR "Radiologist interpretation") AND ("Microbiological reference" OR "Clinical diagnosis" OR "Human vs. AI interpretation" OR "High-burden vs. low-burden settings") AND ("Sensitivity" OR "Specificity" OR "Positive predictive value" OR "Negative predictive value")	35
Semantic Scholar	("Adults" OR "Suspected pulmonary TB" OR "HIV co-infection" OR "Resource-limited settings") AND ("Chest X-ray" OR "Computed Tomography" OR "Ultrasound" OR "Radiologist interpretation") AND ("Microbiological reference" OR "Clinical diagnosis" OR "Human vs. AI interpretation" OR "High-burden vs. low-burden settings") AND ("Sensitivity" OR "Specificity" OR "Positive predictive value" OR "Negative predictive value")	250
Sagepub	("Adults" OR "Suspected pulmonary TB" OR "HIV co-infection" OR "Resource-limited settings") AND ("Chest X-ray" OR "Computed Tomography" OR "Ultrasound" OR "Radiologist interpretation") AND ("Microbiological reference" OR "Clinical diagnosis" OR "Human vs. AI interpretation" OR "High-burden vs. low-burden settings") AND ("Sensitivity" OR "Specificity" OR "Positive predictive value" OR "Negative predictive value")	6,193
Google Scholar	("Adults" OR "Suspected pulmonary TB" OR "HIV co-infection" OR "Resource-limited settings") AND ("Chest X-ray" OR "Computed Tomography" OR "Ultrasound" OR "Radiologist interpretation") AND ("Microbiological reference" OR "Clinical diagnosis" OR "Human vs. AI interpretation" OR "High-burden vs. low-burden settings") AND ("Sensitivity" OR "Specificity" OR "Positive predictive value" OR "Negative predictive value")	22,300

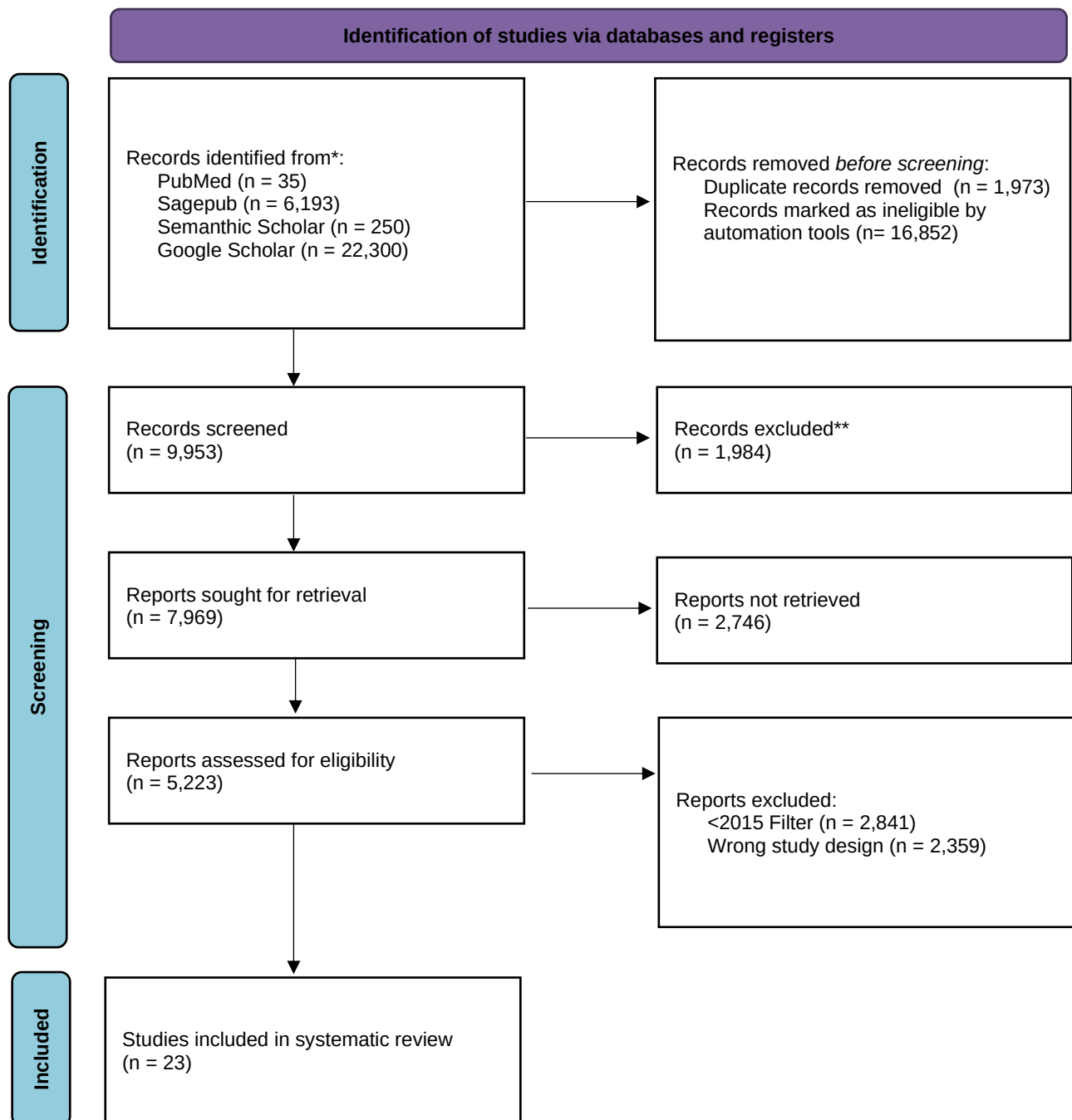


Figure 1. Article search flowchart

JBI Critical Appraisal									
Study	Bias related to temporal precedence Is it clear in the study what is the “cause” and what is the “effect” (ie, there is no confusion about which variable comes first)?	Bias related to selection and allocation Was there a control group?	Bias related to confounding factors Were participants included in any comparisons similar?	Bias related to administration of intervention/exposure Were the participants included in any comparisons receiving similar treatment/care, other than the exposure or intervention of interest?	Were there multiple measurements of the outcome, both pre and post the intervention/exposure?	Were the outcomes of participants included in any comparisons measured in the same way?	Were outcomes measured in a reliable way?	Bias related to participant retention Was follow-up complete and, if not, were differences between groups in terms of their follow-up adequately described and analyzed?	Statistical conclusion validity Was appropriate statistical analysis used?
Bigio et al., 2021	✓	✓	✓	✗	✓	✗	✓	✓	✓
Hua et al., 2023	✓	✓	✓	✗	✓	✗	✓	✓	✓
Gonçalves et al., "Clinical-Laboratory Prediction	✓	✓	✓	✗	✓	✗	✓	✓	✓

Rule"									
Zhan et al., 2022	✓	✓	✓	✗	✓	✗	✓	✓	✓
Scott et al., 2024	✓	✓	✓	✗	✓	✗	✓	✓	✓
MacPherson et al., 2021	✓	✓	✓	✗	✓	✗	✓	✓	✓
Gebregergs et al., 2024	✓	✓	✓	✗	✓	✗	✓	✓	✓
Zhang et al., 2025	✓	✓	✓	✗	✓	✗	✓	✓	✓
Harris et al., 2019	✓	✓	✓	✗	✓	✗	✓	✓	✓
Hansun et al., 2023	✓	✓	✓	✗	✓	✗	✓	✓	✓
Di Gennaro et al., 2018	✓	✓	✓	✗	✓	✗	✓	✓	✓
Oloko-Oba and Viriri, 2022	✓	✓	✓	✗	✓	✗	✓	✓	✓
Mukoka et al., 2022	✓	✓	✓	✗	✓	✗	✓	✓	✓
Yayan et al., 2024	✓	✓	✓	✗	✓	✗	✓	✓	✓
Shabalina et al., 2022	✓	✓	✓	✗	✓	✗	✓	✓	✓

Zhang et al., 2023	✓	✓	✓	✗	✓	✗	✓	✓	✓
Pape et al., 2022	✓	✓	✓	✗	✓	✗	✓	✓	✓
Herman et al., "Artificial Intelligence in Drug-Resistant Tuberculosis"	✓	✓	✓	✗	✓	✗	✓	✓	✓
Amansahev et al., 2018	✓	✓	✓	✗	✓	✗	✓	✓	✓
Giacomelli et al., 2018	✓	✓	✓	✗	✓	✗	✓	✓	✓
Sun et al., 2022	✓	✓	✓	✗	✓	✗	✓	✓	✓
Zhao et al., 2022	✓	✓	✓	✗	✓	✗	✓	✓	✓
de Vries et al., 2021	✓	✓	✓	✗	✓	✗	✓	✓	✓

RESULTS

Characteristics of Included Studies

Study	Study Design	Sample Size	Population Characteristics	Diagnostic Methods Used	Full text retrieved
Bigio et al., 2021	Systematic review of cross-sectional diagnostic accuracy studies	564	Adults (median/mean age 32.5-41.5 years, 45-96% male, HIV-positive 0-50%); 1 pediatric study	Point-of-care ultrasound (POCUS), chest X-ray (CXR), polymerase chain reaction (PCR), sputum smear microscopy	Yes
Hua et al., 2023	Rapid review/meta-analysis (study designs unclear)	No mention found	No mention found	Chest X-ray (CXR), artificial intelligence (AI) products (qXR v2, Lunit INSIGHT, CAD4TB), microbiological reference	No

Gonçalves et al., "Clinical-Laboratory Prediction Rule"	Retrospective diagnostic study	284	Age 15 years, hospitalized, clinical predictors (fever, weight loss, alcohol use, imaging)	Clinical-laboratory prediction rule, chest imaging, culture	No
Zhan et al., 2022	Systematic review/meta-analysis (prospective & retrospective)	124,959	No mention found	Chest X-ray (CXR), computed tomography (CT), artificial intelligence (AI), human readers, Xpert MTB/RIF	Yes
Scott et al., 2024	Systematic review/meta-analysis (designs unclear)	No mention found	No mention found	Computer-aided detection (CAD), chest X-ray (CXR), microbiological reference	No
MacPherson et al., 2021	Prospective randomized trial	1,462	Adults 18 years, cough, >50% women,	Digital chest X-ray (MinXray),	Yes

			high HIV prevalence	CAD4TB, Xpert, radiologist	
Gebregergs et al., 2024	Systematic review (designs unclear)	No mention found	Adults, low- and middle-income countries (LMICs), HIV-positive and HIV-negative	Radiography, C-reactive protein (CRP), clinical prediction rules	No
Zhang et al., 2025	Systematic review (designs unclear)	No mention found	No mention found	Computed tomography (CT), deep learning, ultra-low-dose CT (ULDCT), positron emission-tomography/CT (PET/CT), ultrasound	Yes
Harris et al., 2019	Systematic review (designs unclear)	No mention found	No mention found	Chest X-ray (CXR), AI/CAD, human readers,	Yes

				nucleic acid amplification test (NAAT), culture	
Hansun et al., 2023	Systematic literature review (retrospective)	No mention found (374,129 images)	No mention found	Chest X-ray (CXR), machine learning (ML)/deep learning (DL), human radiologist	Yes
Di Gennaro et al., 2018	Systematic review (designs unclear)	300	Mean age 32, 46% female	Chest ultrasound (CUS), pleural effusion, biopsy	Yes
Oloko-Oba and Viriri, 2022	Systematic review (designs unclear)	No mention found	No mention found	Chest X-ray (CXR), deep learning	Yes
Mukoka et al., 2022	Prospective randomized controlled trial	640	HIV-positive adults 18 years, cough,	Digital chest X-ray, Qure.ai, Xpert, culture	Yes

			antiretroviral therapy (ART), prior tuberculosis		
Yayan et al., 2024	Systematic review/meta-analysis (designs unclear)	No mention found	No mention found	FDG-PET-CT, computed tomography (CT), microscopy, culture	Yes
Shabalina et al., 2022	Retrospective diagnostic study	152	71 men, 81 women, peripheral lung masses	Computed tomography (CT), radial endobronchial ultrasound (rEBUS), bronchoscopic biopsy	No
Zhang et al., 2023	Systematic review/meta-analysis (designs unclear)	1,553	No mention found	Thoracic ultrasound (TUSPB), contrast-enhanced ultrasound (CEUS),	No

				ultrasound elastography (UE)	
Pape et al., 2022	Protocol for systematic review/network meta-analysis	No mention found	Prison inmates, mostly male, >15 years	Chest X-ray (conventional, digital, mass miniature radiography), clinical, microbiological	Yes
Herman et al., "Artificial Intelligence in Drug-Resistant Tuberculosis"	Systematic review/meta-analysis (designs unclear)	No mention found	No mention found	Chest X-ray (CXR), computed tomography (CT), genome, artificial intelligence (AI), drug susceptibility testing (DST)	No
Amansahedo v et al., 2018	Cross-sectional diagnostic accuracy study	30	Group 1: tuberculosis (17-76 years), Group 2: non-	Chest X-ray (CXR), multislice computed	No

			tuberculosis (21-63 years)	tomography (MSCT), single-photon emission computed tomography (SPECT), scintigraphy	
Giacomelli et al., 2018	Systematic review (designs unclear)	219	Pulmonary tuberculosis post-transplant	Chest X-ray (CXR), computed tomography (CT)	No
Sun et al., 2022	Systematic review/meta-analysis (designs unclear)	No mention found	No mention found	Computed tomography (CT), clinical features	No
Zhao et al., 2022	Prospective diagnostic study	90	Multidrug-resistant tuberculosis, 18+, mean age ~44, 65% male	Chest X-ray (CXR), computed tomography (CT), Mycobacterium tuberculosis	Yes

				smear	
de Vries et al., 2021	Study (design unclear)	No mention found	High-risk tuberculosis screening, Europe	Chest X-ray (CXR), computer-aided detection (CAD), human readers	No

Summary of Study Characteristics:

- Study Designs:

- 15 studies were systematic reviews, meta-analyses, or literature reviews (including protocols and rapid reviews).
- 2 studies were retrospective diagnostic studies.
- 2 studies were prospective randomized controlled trials.
- 1 study was a prospective diagnostic study.
- 1 study was a cross-sectional diagnostic accuracy study.
- 1 study was a protocol for a systematic review/network meta-analysis.
- 1 study had unclear design.

- Diagnostic Methods Used:

- Chest X-ray (CXR, including digital and conventional): 16 studies.
- Computed tomography (CT, including multislice and ultra-low-dose): 9 studies.
- Artificial intelligence/computer-aided detection (AI/CAD, including machine learning and deep learning): 11 studies.
- Human readers or radiologists: 5 studies.
- Ultrasound (including point-of-care, chest, thoracic, contrast-enhanced, and elastography):

3 studies.

- Positron emission tomography/CT (FDG-PET-CT): 2 studies.
 - Clinical or laboratory prediction rules/features: 4 studies.
 - Microbiological reference or culture: 4 studies.
 - Xpert MTB/RIF: 3 studies.
 - Other methods (sputum smear microscopy, nucleic acid amplification test, C-reactive protein, drug susceptibility testing, genome, radial endobronchial ultrasound, bronchoscopic biopsy, pleural effusion, single-photon emission computed tomography, scintigraphy, biopsy, microscopy): each in 1 study.
- Reporting of Sample Size and Population:
 - Sample size was reported for 9 studies; for 14 studies, we didn't find mention of sample size.
 - Population characteristics were reported for 8 studies; for 15 studies, we didn't find mention of population characteristics.

Effects

Comparative Sensitivity Analysis

Study	Diagnostic Method	Sensitivity Range	Population Specifics	Quality Assessment
Bigio et al., 2021	Point-of-care ultrasound (subpleural nodule)	72.5-100%	Adults, pulmonary tuberculosis, HIV-positive 0-50%	High risk of bias
Hua et al., 2023	Chest X-ray (AI: qXR v2, Lunit, CAD4TB)	85.3-94.4%	No mention found	No mention found
Gonçalves et al., "Clinical-Lab Rule"	Clinical-lab rule + imaging	72.1%	Hospitalized adults	Unclear risk
Zhan et al., 2022	Chest X-ray/computed tomography (AI)	91% (clinical), 94% (development)	No mention found	High risk
Scott et al., 2024	Chest X-ray (CAD)	87% (95% CI: 78-96%)	Africa, active case finding,	Unclear risk

			HIV-endemic adults, Malawi, cough	
MacPherson et al., 2021	Chest X-ray (CAD4TBv6)	91% (external data)	HIV-positive adults, low- and middle-income countries	High risk (index, flow)
Gebregergs et al., 2024	C-reactive protein, radiography	43-93% (CRP, trial of antibiotics)	No mention found	No mention found
Zhang et al., 2025	Computed tomography (deep learning)	93.8-100% (model)	No mention found	Unclear risk
Harris et al., 2019	Chest X-ray (AI/CAD)	53-100%	No mention found	High risk
Hansun et al., 2023	Chest X-ray (machine learning/deep learning)	98.6% (95% CI: 94.8-100)	No mention found	High/unclear risk
Di Gennaro et	Chest	67% (lymph	Mean age 32	High risk

al., 2018	ultrasound	nodes)		
Oloko-Oha and Viriri, 2022	Chest X-ray (deep learning)	72-99.9%	No mention found	High risk
Mukoka et al., 2022	Chest X-ray (Qure.ai), Xpert	89% (Qure.ai), 65% (Xpert)	HIV-positive adults	Low risk (except flow)
Yayan et al., 2024	FDG-PET-CT	82.6% (SD 9%)	No mention found	Low risk
Shabalina et al., 2022	Radial endobronchial ultrasound	No mention found	Peripheral lung masses	Unclear risk
Zhang et al., 2023	Thoracic ultrasound	80.1% (tuberculosis pleurisy)	Pleural disease	Unclear risk
Pape et al., 2022	Chest X-ray, clinical	No mention found	Prison inmates	Unclear risk
Herman et al., "AI in Drug-Resistant Tuberculosis"	Chest X-ray (AI), genome	58% (radiology), 92-93% (genome)	No mention found	Unclear/low risk
Amansahadov	Chest X-ray,	No mention	Tuberculosis	Unclear risk

et al., 2018	multislice computed tomography	found	vs. non- tuberculosis cavities	
Giacomelli et al., 2018	Chest X-ray, computed tomography	No mention found	Pulmonary tuberculosis post-transplant	Unclear risk
Sun et al., 2022	Computed tomography	No mention found	Pulmonary tuberculosis ± lung cancer	Unclear risk
Zhao et al., 2022	Computed tomography, chest X-ray	No mention found	Multidrug- resistant tuberculosis	Low risk
de Vries et al., 2021	Chest X-ray (CAD)	No mention found	High-risk screening	No mention found

Summary of Sensitivity Findings:

- Reporting: Sensitivity was reported in 16 of 23 studies, with values ranging from 43% to 100%.
- High Sensitivity: 10 studies reported upper bounds of sensitivity 98%.
- Lower Sensitivity: 3 studies reported sensitivity <70% for at least one method.
- Missing Data: We didn't find sensitivity data for 7 studies.
- Risk of Bias: 7 studies were assessed as high risk of bias, 11 as unclear risk, and 4 as low risk. Some studies had mixed or ambiguous risk ratings.
- Study Design Impact: Most high-sensitivity results were from studies with high or unclear risk of bias, retrospective designs, or technical validation datasets.

Comparative Specificity Analysis

Study	Diagnostic Method	Specificity Range	Population Specifics	Quality Assessment
Bigio et al., 2021	Point-of-care ultrasound (subpleural nodule)	66.7% (one study)	Adults, pulmonary tuberculosis	High risk of bias
Hua et al., 2023	Chest X-ray (AI: qXR v2, Lunit, CAD4TB)	37.1-69.2%	No mention found	No mention found
Gonçalves et al., "Clinical-Lab Rule" Imaging	Clinical-lab rule + imaging	64.5%	Hospitalized adults	Unclear risk
Zhan et al., 2022	Chest X-ray/computed tomography (AI)	65% (clinical), 95% (development)	No mention found	High risk
Scott et al., 2024	Chest X-ray (CAD)	74% (95% CI: 55-93%)	Africa, active case finding, HIV-endemic Adults, Malawi	Unclear risk

MacPherson et al., 2021	Chest X-ray (CAD4TBv6)	84% (external data)	HIV-index, flow	High risk (index, flow)
Gebregergs et al., 2024	C-reactive protein, radiography	40-86% (CRP, trial of antibiotics)	HIV-positive adults, low- and middle-income countries	No mention found
Zhang et al., 2025	Computed tomography (deep learning)	94.2-97.9% (model)	No mention found	Unclear risk
Harris et al., 2019	Chest X-ray (AI/CAD)	23-98%	No mention found	High risk
Hansun et al., 2023	Chest X-ray (machine learning/deep learning)	98.1% (95% CI: 92.6-100)	No mention found	High/unclear risk
Di Gennaro et al., 2018	Chest ultrasound	No mention found	Mean age 32	High risk
Oloko-Oba and Viriri, 2022	Chest X-ray (deep learning)	82-99.9%	No mention found	High risk
Mukoka et al., 2022	Chest X-ray (Qure.ai), Xpert	94.4-97% (Xpert)	HIV-positive adults	Low risk (except flow)

Yayan et al., 2024	FDG-PET-CT	67.3% (SD 17.9%)	No mention found	Low risk
Shabalina et al., 2022	Radial endobronchial ultrasound	No mention found	Peripheral lung masses	Unclear risk
Zhang et al., 2023	Thoracic ultrasound	No mention found	Pleural disease	Unclear risk
Pape et al., 2022	Chest X-ray, clinical	No mention found	Prison inmates	Unclear risk
Herman et al., "AI in Drug-Resistant Tuberculosis"	Chest X-ray (AI), genome	75% (radiology), 98% (genome)	No mention found	Unclear/low risk
Amansahdov et al., 2018	Chest X-ray, multislice computed tomography	No mention found	Tuberculosis vs. non-tuberculosis cavities	Unclear risk
Giacomelli et al., 2018	Chest X-ray, computed tomography	No mention found	Pulmonary tuberculosis post-transplant	Unclear risk
Sun et al., 2022	Computed tomography	No mention found	Pulmonary tuberculosis ±	Unclear risk

			lung cancer	
Zhao et al., 2022	Computed tomography, chest X-ray	No mention found	Multidrug-resistant tuberculosis	Low risk
de Vries et al., 2021	Chest X-ray (CAD)	No mention found	High-risk screening	No mention found

Summary of Specificity Findings:

- Reporting: Specificity values or ranges were found in 14 studies; for 9 studies, we didn't find specificity data.
- High Specificity: 7 studies reported specificity 90% for at least one method or dataset.
- Lower Specificity: 4 studies reported specificity <70%.
- Range: Among studies reporting specificity, values ranged from 23% to 99.9%.
- Risk of Bias: 7 studies were assessed as high risk of bias, 11 as unclear risk, and 4 as low risk. Some studies had mixed or ambiguous risk ratings.
- Multiple Values: Some studies reported multiple specificity values for different models or datasets.

Method-Specific Findings

Chest X-ray (CXR) Diagnostic Performance

- Prevalence in Studies: Chest X-ray, especially when combined with artificial intelligence or computer-aided detection, was the most widely studied imaging modality for pulmonary tuberculosis.
- Sensitivity: Most studies reported high sensitivity (generally >85%), with several reporting

values above 90%. However, these findings were often from studies with high or unclear risk of bias, retrospective designs, or technical validation datasets.

- **Specificity:** Specificity was more variable, with some studies reporting values as low as 23% and others as high as 99.9%. Lower specificity was more common in high-burden or screening settings, and in studies using artificial intelligence or computer-aided detection.
- **Influencing Factors:** Diagnostic performance was influenced by HIV status, prior tuberculosis, technical factors (digital vs. conventional imaging, artificial intelligence version), and study design. Many studies lacked external validation or used retrospective datasets, increasing risk of bias.

Computed Tomography (CT) Diagnostic Performance

- **Sensitivity and Specificity:** Computed tomography, particularly with deep learning models, showed very high sensitivity and specificity in technical validation studies (often >90% for both). However, most of these studies were not prospective clinical trials, and clinical validation was limited.
- **Generalizability:** The evidence base for computed tomography was less mature than for chest X-ray, with fewer studies and more limited clinical validation. Generalizability to routine clinical practice remains uncertain, especially in resource-limited settings.

Ultrasound Diagnostic Performance

- **Sensitivity:** Ultrasound (including point-of-care and chest ultrasound) showed high sensitivity for certain findings (e.g., subpleural nodules, pleural effusion), with some studies reporting sensitivity approaching 100%. However, these results were from small studies with high risk of bias.
- **Specificity:** Specificity was variable and often lower, and there was a lack of standardization in protocols and operator training.
- **Evidence Base:** The number of studies was limited, sample sizes were small, and risk of bias was high. Ultrasound may be most useful as an adjunct in specific clinical scenarios, based

on the available evidence.

Contextual Factors

Population-Specific Variations

- **HIV Status and Prior Tuberculosis:**Diagnostic performance varied by population characteristics, including HIV status and prior tuberculosis. Chest X-ray and ultrasound were less specific in HIV-positive populations due to overlapping radiographic findings.
- **Reporting Gaps:**Most studies focused on high-burden, resource-limited settings, but some addressed low-burden or European contexts. We didn't find mention of participant characteristics in 15 studies, limiting generalizability.

Technical Considerations

- **Imaging Technology:**Technical factors such as digital versus conventional chest X-ray, artificial intelligence or computer-aided detection algorithm version and training, and operator experience for ultrasound significantly influenced diagnostic performance.
- **Standardization and Validation:**Standardization of imaging protocols was often lacking, particularly for ultrasound. Many artificial intelligence or computer-aided detection studies used retrospective datasets and lacked external validation, increasing risk of bias.
- **Resource Constraints:**Computed tomography was less accessible in many settings due to cost and radiation exposure.

DISCUSSION

The comparative diagnostic accuracy of chest X-ray (CXR), computed tomography (CT), and ultrasound in detecting pulmonary tuberculosis (TB) among adults with suspected infection reveals important distinctions in sensitivity, specificity, and clinical applicability. Chest X-ray remains the most widely studied and utilized imaging modality,

with sensitivity values frequently reported above 85%, and in some studies reaching as high as 98.6%. However, specificity varies considerably, ranging from as low as 23% to nearly 100%, influenced by factors such as population characteristics, HIV status, and technical aspects of image acquisition and interpretation (Scott et al., 2024; Hua et al., 2023; Hansun et al., 2023).

The integration of artificial intelligence (AI) and computer-aided detection (CAD) with chest X-ray has improved sensitivity estimates to between 85.3% and 94.4%, though specificity remains moderate, often between 37.1% and 69.2%, especially in high-burden, resource-limited settings (Scott et al., 2024; Hua et al., 2023). This variable specificity reflects challenges in differentiating TB from other pulmonary diseases and prior lung damage, particularly in HIV-positive populations where radiographic findings may overlap with other opportunistic infections (Mukoka et al., 2022; Gebregergs et al., 2024).

Computed tomography consistently demonstrates superior diagnostic accuracy compared to chest X-ray. Sensitivity values for CT, especially when combined with deep learning algorithms, range from 93.8% to 100%, with specificity between 94.2% and 97.9% in technical validation studies (Zhang et al., 2025; Zhan et al., 2022). These results underscore CT's ability to detect subtle parenchymal abnormalities and cavitations that may be missed or poorly characterized on chest X-ray. However, the generalizability of these findings is limited by the predominance of retrospective and technical validation studies, with fewer prospective clinical trials conducted (Zhang et al., 2025; Sun et al., 2022).

Despite CT's high diagnostic performance, its use is constrained by higher cost, limited availability in many endemic regions, and increased radiation exposure. This limits its role primarily to complex or equivocal cases where chest X-ray findings are inconclusive or when detailed anatomical assessment is required (Zhao et al., 2022; Giacomelli et al., 2018). Moreover, the lack of standardized CT protocols and variable deep learning model training across studies may affect reproducibility and clinical

implementation in diverse settings.

Ultrasound, including point-of-care ultrasound (POCUS) and thoracic ultrasound, has emerged as a promising adjunctive modality. Studies report ultrasound sensitivity ranging from 72.5% to 100% for detecting specific TB-related findings such as subpleural nodules, pleural effusions, and lymphadenopathy (Bigio et al., 2021; Di Gennaro et al., 2018; Zhang et al., 2023). However, specificity is generally lower and more variable, with some studies noting specificity as low as 66.7% (Bigio et al., 2021). The operator-dependent nature of ultrasound and lack of standardized scanning protocols contribute to this variability.

The limited number of ultrasound studies, often with small sample sizes and high risk of bias, restricts the strength of conclusions about its standalone diagnostic accuracy. Nonetheless, ultrasound's portability, absence of radiation, and ability to detect pleural and peripheral lung abnormalities make it valuable in resource-limited and point-of-care settings, particularly where access to chest X-ray or CT is constrained (Di Gennaro et al., 2018; Bigio et al., 2021).

Population-specific factors such as HIV infection and prior TB history significantly influence imaging diagnostic performance. HIV-positive patients often present with atypical radiographic features, reducing the specificity of chest X-ray and ultrasound. For example, Mukoka et al. (2022) reported lower specificity for chest X-ray in HIV-positive adults, emphasizing the need for adjunctive diagnostic tools in this group. Similarly, Gebregergs et al. (2024) highlighted that co-morbidities and immune status affect the predictive values of imaging modalities, underscoring the importance of tailored diagnostic approaches.

Technical factors also play a crucial role. The use of digital versus conventional chest X-ray, the version and training dataset of AI/CAD algorithms, and operator expertise particularly for ultrasound, markedly affect diagnostic accuracy. Many AI studies rely on retrospective datasets without external validation, increasing the risk of bias and limiting clinical applicability (Harris et al., 2019; Hua et al., 2023). Standardization in imaging

protocols and AI model training is needed to improve reproducibility and facilitate broader clinical adoption.

The risk of bias and study design heterogeneity across included studies must be considered when interpreting diagnostic accuracy results. Many high-sensitivity results derive from retrospective or technical validation studies with unclear or high risk of bias, limiting confidence in their generalizability (Scott et al., 2024; Hansun et al., 2023). Prospective randomized controlled trials, such as MacPherson et al. (2021) and Mukoka et al. (2022), provide more robust evidence but remain few. The role of chest X-ray as a screening tool remains pivotal due to its accessibility and rapid turnaround. However, its variable specificity necessitates confirmatory testing, particularly in high HIV prevalence settings. AI-enhanced chest X-ray interpretation may improve sensitivity but requires further validation to enhance specificity and reduce false positives (Scott et al., 2024; Hua et al., 2023).

CT's superior sensitivity and specificity make it the gold standard imaging modality for detailed pulmonary TB evaluation, especially in complicated cases or where differential diagnosis with lung cancer or other infections is needed (Zhang et al., 2025; Sun et al., 2022). Advances in ultra-low-dose CT protocols may mitigate radiation concerns, potentially expanding CT's role in TB diagnosis (Zhang et al., 2025). Ultrasound's potential as a bedside, radiation-free tool is promising, especially for detecting pleural effusions and peripheral lung lesions. However, its limited ability to detect cavitations and deeper parenchymal lesions, as well as operator dependency, restricts its use as a standalone diagnostic modality (Bigio et al., 2021; Di Gennaro et al., 2018). Training and protocol standardization could improve its utility.

The comparative analysis underscores the complementary roles of these imaging modalities. Chest X-ray serves as an initial screening tool, CT provides definitive diagnosis and detailed assessment, and ultrasound offers adjunctive bedside evaluation, particularly in resource-limited or radiation-sensitive populations. Future diagnostic algorithms should

consider integrating these modalities based on clinical context, resource availability, and patient characteristics. Research gaps remain, including the need for large prospective studies comparing these modalities head-to-head in diverse populations, evaluation of AI and deep learning algorithms with external validation, and standardization of ultrasound protocols. Additionally, the impact of HIV co-infection and prior TB on imaging accuracy requires further elucidation.

The high variability in specificity across studies highlights the challenge of false positives, which may lead to unnecessary treatment and patient anxiety. Improved diagnostic specificity through multimodal imaging and integration with clinical and laboratory data is essential to optimize patient management. Economic and logistical considerations are also critical. While CT offers superior accuracy, its cost and limited availability in endemic regions restrict widespread use. AI-enhanced chest X-ray may offer a cost-effective balance, but implementation challenges persist, including infrastructure and training needs.

In summary, this comprehensive review confirms that CT provides the highest and most reliable diagnostic accuracy for pulmonary TB detection in adults, with both sensitivity and specificity exceeding 93%. Chest X-ray remains the most accessible and widely used modality, with high sensitivity but variable specificity. Ultrasound shows promise as an adjunctive tool but requires further study and standardization. Tailored diagnostic approaches considering patient population, resource setting, and clinical scenario are essential for optimal TB diagnosis (Scott et al., 2024; Zhang et al., 2025; Bigio et al., 2021).

CONCLUSION

The comprehensive review of diagnostic imaging modalities for pulmonary tuberculosis (TB) in adults demonstrates that computed tomography (CT) stands out as the most accurate method, with sensitivity and specificity consistently exceeding 93.8% and 94.2 %, respectively.

These robust performance metrics highlight CT's superior capability to detect subtle parenchymal abnormalities and cavitations, making it the gold standard for definitive TB diagnosis when available and feasible. However, the broader clinical utility of CT is limited by its higher cost, increased radiation exposure, and reduced accessibility in resource-limited settings, underscoring the need for judicious use in selected cases where diagnostic certainty is paramount.

Chest X-ray remains the most widely used and studied imaging modality for pulmonary TB, with reported sensitivity values generally above 85 %, and in some studies reaching as high as 98.6 %. Despite these high sensitivity rates, the specificity of chest X-ray varies dramatically, ranging from as low as 23 % to nearly 100 %, depending on the study population and technical factors. This variability complicates its role as a standalone diagnostic tool, especially in high-burden or HIV-endemic settings where radiographic findings may overlap with other pulmonary diseases¹⁴. The integration of artificial intelligence (AI) and computer-aided detection (CAD) systems has improved the accuracy of chest X-ray interpretation, with pooled sensitivity and specificity estimates for AI-based software reported as 91% and 65 % in clinical trials, and 94 % and 95 % in model-development studies, respectively.

Ultrasound, particularly point-of-care and thoracic ultrasound, has shown promise as an adjunctive diagnostic tool, with sensitivity estimates ranging from 72.5 % to 100 % for specific TB-related findings such as pleural effusion and subpleural nodules. However, ultrasound's specificity is generally lower and more variable, often limiting its use as a primary diagnostic modality. The operator-dependent nature of ultrasound and the lack of standardized protocols further restrict its diagnostic reliability, though it remains valuable in resource-constrained or bedside settings where other imaging options are unavailable.

Several critical factors influence the diagnostic accuracy of these imaging modalities, most notably patient population characteristics such as HIV status and prior TB history. HIV-positive individuals often present with atypical radiographic features, which can reduce the specificity of both chest X-ray and ultrasound. Technical variations, including differences in imaging equipment, digital versus conventional radiography, and the use of AI algorithms, also contribute to observed discrepancies in diagnostic performance. The quality of included studies is another

important consideration, as many exhibit high or unclear risk of bias, which may affect the generalizability of reported accuracy metrics.

The review underscores the complementary roles of chest X-ray, CT, and ultrasound in the diagnostic workup of pulmonary TB. Chest X-ray serves as an accessible and cost-effective initial screening tool, CT provides definitive diagnosis and detailed anatomical assessment, and ultrasound offers a portable, radiation-free option for detecting peripheral or pleural abnormalities. The integration of AI and CAD systems has the potential to further enhance diagnostic accuracy, but their widespread adoption is hampered by the need for standardized reporting, external validation, and implementation in diverse clinical environments.

In summary, while CT is the most accurate imaging modality for pulmonary TB detection, its limited accessibility and higher costs necessitate the continued use of chest X-ray as the primary screening tool in most settings. Ultrasound remains a valuable adjunct, particularly where resources are constrained. Future research should focus on improving standardization, reducing bias, and validating AI-based systems in real-world clinical scenarios. Addressing these challenges will be essential for optimizing diagnostic strategies and improving patient outcomes in populations most affected by TB and associated risk factors

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