Health Technology Assessment of AI-Assisted CXR for Interpretation for Tuberculosis: A Rapid Health Technology Assessment

Health Technology Assessment in India (HTAIn)
Indian Institute of Public Health Gandhinagar

INDIAN INSTITUTE of PUBLIC HEALTH GANDHINAGAR
ESTABLISHED BY GOVT. OF GUJARAT AND PHFI

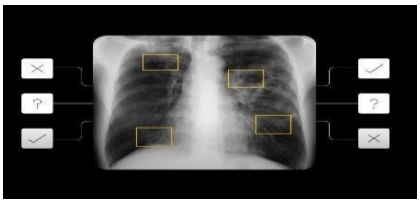
Policy Brief

Executive Summary

- One of the major barriers in the treatment and management of Tuberculosis is the early Diagnosis and treatment of Tuberculosis. In the recent times, with the emerging technological advancements, the use of Artificial Intelligence (AI) has gained significant importance and has been employed in the context of tuberculosis screening as well.
- The study was conducted to determine the interpretation and screening accuracy of two AI Assisted CXR Interpretation tools namely qXR from Qure.AI and Genki from Deeptek; with manual interpretation of CXR using Conventional Digital X-Ray Methods along with to find out the cost-effectiveness analysis of AI Assisted CXR in comparison with Manual Interpretation of CXR.
- The findings of the study indicated that the Incremental Cost-Effectiveness Ratio (ICER) for qXR was found to be -9,864.77 INR per case screened / interpreted. Both ICER values are below the per capita GDP of India for the year 2022 (1,97,440.48 INR), indicating cost-effectiveness.
- The study concluded that AI enabled interpretation could be a potential solution to the issue of human resource constraints and reduce the delays in the diagnosis and treatment of Tuberculosis. The study also reported the pooled sensitivity and specificity of the AI interventions from existing literature, which were found to be 90% and 68% respectively which meets the non-inferior accuracy criteria as per WHO consolidated guidelines on systematic screening for tuberculosis and hence might be looked up as a potential alternative in resource constraint settings.

Policy Recommendations

- Both interventions fall within the acceptable cost-effectiveness range which can enhance screening procedures by addressing the issue of human resource constraints and reducing the delays in the diagnosis and treatment of Tuberculosis.



Background and Gap in Literature

- Tuberculosis (TB) remains a pervasive global health challenge, claiming millions of lives annually and posing a substantial burden, particularly in countries like India, where it is a leading cause of mortality. India has set ambitious targets through its National Tuberculosis Elimination Program to achieve "End TB Strategies" by 2025.
- One of the major barriers in the treatment and management of Tuberculosis is the early Diagnosis and treatment of Tuberculosis. In the recent times, with the emerging technological advancements, the use of Artificial Intelligence (AI) has gained significant importance and has been employed in the context of tuberculosis screening as well.
- AI-assisted solutions have the potential to revolutionize TB detection in radiography, contributing to improved patient outcomes and global public health efforts. This assessment explores the transformative impact of AI-assisted CXR interpretation tool for tuberculosis and its cost effectiveness. Two tools were taken in the assessment: 1) qXR, Qure.Ai and 2) Genki, DeepTek

Aims and Objective

The study was conducted to determine the interpretation and screening accuracy of two AI Assisted CXR Interpretation tools namely qXR from Qure.AI and Genki from Deeptek; with manual interpretation of CXR using Conventional Digital X-Ray Methods along with to find out the cost-effectiveness analysis of AI Assisted CXR in comparison with Manual Interpretation of CXR.

PICO

- **P**opulation: Patients screened for potential TB-related chest pathology
- **I**ntervention: AI-Assisted interpretation tools for chest X-Ray: qXR and Genki
- **C**omparator: Manual Interpretation by Radiologists of CXR taken by Digital X-Ray machine
- **O**utcome: 1) Diagnostic Accuracy in interpretation using AI Assisted CXR tools in compared to conventional method. 2) ICER: Cost per Case Interpreted/Screened

Methods and Approach

- The study employed cost-effective analysis based on an economic model, conducted from a health system perspective.
- Diagnostic accuracy: Pooled sensitivity and specificity were used combining the results of 6 studies data sets.
- Cost per Cases Interpreted with the help of Capital cost (Software/License costs, Deployment and Integration, Dedicated client support, Life cycle management) and Operational cost (HR, Software maintenance, Printing cost & other miscellaneous costs)
- Source of Information: For Intervention, Service Providers and User department and For Comparator, Secondary data from HTAIn RRC-IIPHG CXR costing study were considered for the study.

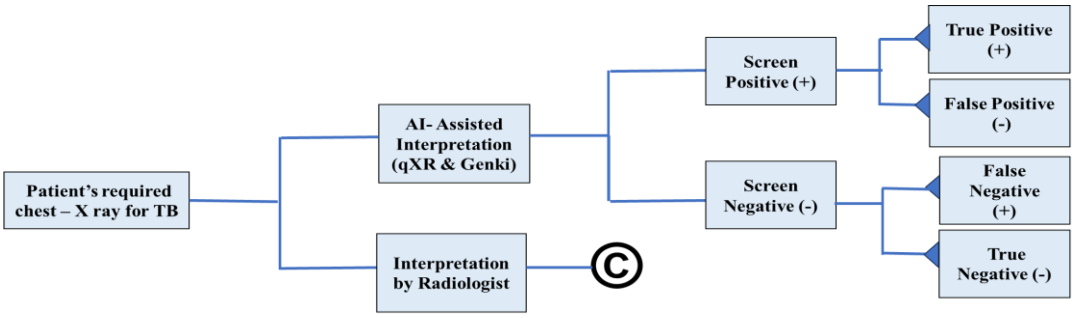


Figure 1: Decision tree model

Table 1: Calculated Pooled Sensitivity and Specificity

	Pooled Sensitivity	Pooled Specificity
For qXR (Intervention)	90.22	68.21
For Genki (Intervention)	90.41	66.38
For Radiologist (Comparator)	88.72	49.61
WHO Minimal requirement for target screening test	> 90	> 70

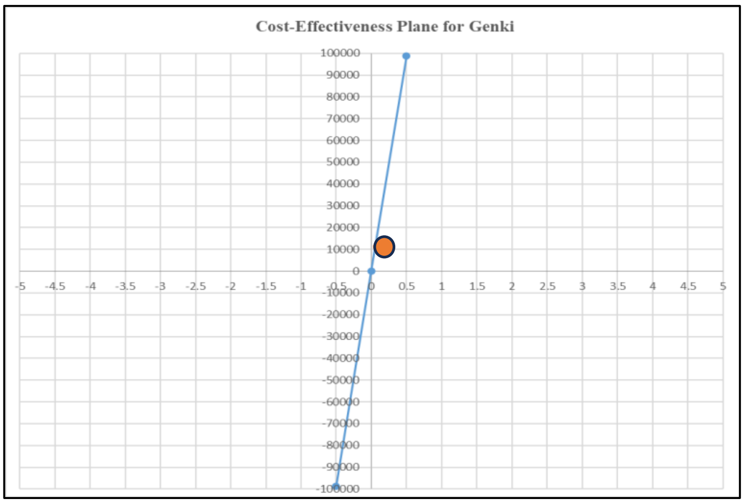


Figure 2 CE Plane for Genki

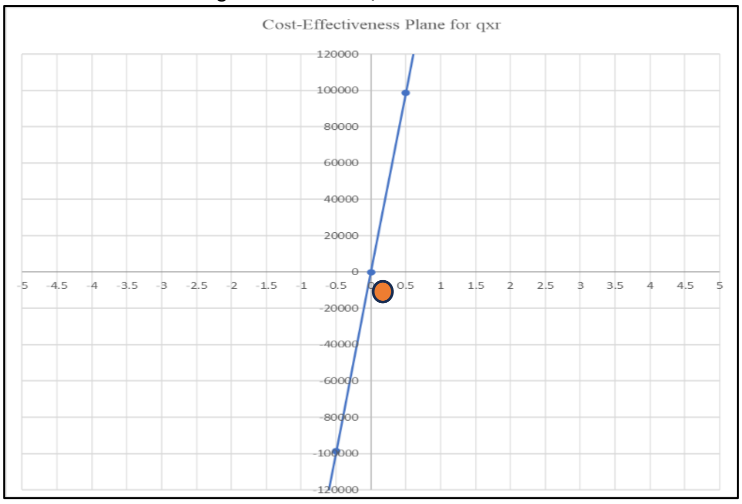


Figure 3 CE Plane for qXR

- Figure 2 and 3 illustrates cost-effectiveness plane. Orange dot indicates ICER value which suggests that the AI solution falls under the dominant quadrant, making intervention acceptable and preferred option.
- The tornado diagram for both the intervention of one-way sensitivity analysis shows that ICER value is slightly changed when the input parameters were changed in multiple indicators.

Results

- The findings of the study indicated that the Incremental Cost-Effectiveness Ratio (ICER) for qXR was found to be -9,864.77 INR per case screened/interpreted, while for Genki, it was 11,286.93 INR per case screened/interpreted. Both ICER values are below the per capita GDP of India for the year 2022 (1,97,440.48 INR), indicating cost-effectiveness.
- For gaining one unit of health benefit, healthcare system can maximum spend an amount of INR 35 and INR 410 for Genki and qXR respectively.

Conclusion

- The study concluded that AI enabled interpretation could be a potential solution to the issue of human resource constraints and reduce the delays in the diagnosis and treatment of Tuberculosis. The study also reported the pooled sensitivity and specificity of the AI interventions from existing literature, which were found to be 90% and 68% respectively which meets the non-inferior accuracy criteria as per WHO consolidated guidelines on systematic screening for tuberculosis and hence might be looked up as a potential alternative in resource constraint settings.

References

1. World Health organization. Global tuberculosis report 2021. https://www.who.int/publications/i/item/9789240037021.
2. WHO. https://www.who.int/publications/i/item/WHO-HTM-TB-2015.19. 2015. The end TB strategy.
3. Muniyandi M, Ramachandran R, Balasubramanian R. Indian Journal of Tuberculosis Costs to patients with tuberculosis treated under DOTS programme.
4. Muniyandi M, Rajeswari R, Balasubramanian R. Estimating provider cost for treating patients with tuberculosis under Revised National Tuberculosis Control Programme (RNTCP). Vol. 12, Indian Journal of Tuberculosis.
5. Muniyandi M, Lavanya J, Karikalan N, Saravanan B, Senthil S, Selvaraju S, et al. Estimating TB diagnostic costs incurred under the National Tuberculosis Elimination Programme: a costing study from Tamil Nadu, South India. Int Health. 2021 Dec 1;13(6):536–44.
6. Rupani MP, Cattamanchi A, Shete PB, Vollmer WM, Basu S, Dave JD. Costs incurred by patients with drug-susceptible pulmonary tuberculosis in semi-urban and rural settings of Western India. Infect Dis Poverty. 2020 Dec 19;9(1):144.
7. Sarin R, Vohra V, Singla N, Thomas B, Krishnan R, Muniyandi M. Identifying costs contributing to catastrophic expenditure among TB patients registered under RNTCP in Delhi metro city in India. Indian Journal of Tuberculosis. 2019 Jan;66(1):150–7.
8. Ananthakrishnan R, Muniyandi M, Jeyaraj A, Palani G, Sathiyasekaran BWC. Expenditure Pattern for TB Treatment among Patients Registered in an Urban Government DOTS Program in Chennai City, South India. Tuberc Res Treat. 2012;2012:1–6.
9. Harris M, Qi A, Jeagal L, Torabi N, Menzies D, Korobitsyn A, et al. A systematic review of the diagnostic accuracy of artificial intelligence-based computer programs to analyze chest x-rays for pulmonary tuberculosis. PLoS One. 2019 Sep 3;14(9):e0221339.

10. Qin ZZ, Ahmed S, Sarker MS, Paul K, Adel ASS, Naheyan T, et al. Tuberculosis detection from chest x-rays for triaging in a high tuberculosis-burden setting: an evaluation of five artificial intelligence algorithms. Lancet Digit Health. 2021 Sep 1;3(9):e543–54.
11. Rajaraman S, Candemir S, Kim I, Thoma G, Antani S. Visualization and interpretation of convolutional neural network predictions in detecting pneumonia in pediatric chest radiographs. Applied Sciences (Switzerland). 2018 Sep 20;8(10).
12. Nijiati M, Ma J, Hu C, Tuersun A, Abulizi A, Kelimu A, et al. Artificial Intelligence Assisting the Early Detection of Active Pulmonary Tuberculosis From Chest X-Rays: A Population-Based Study. Front Mol Biosci. 2022 Apr 8;9.
13. Sreeramareddy CT, Qin ZZ, Satyanarayana S, Subbaraman R, Pai M. Delays in diagnosis and treatment of pulmonary tuberculosis in India: a systematic review. The International Journal of Tuberculosis and Lung Disease. 2014 Mar 1;18(3):255–66.
14. Codlin AJ, Dao TP, Vo LNQ, Forse RJ, Van Truong V, Dang HM, et al. Independent evaluation of 12 artificial intelligence solutions for the detection of tuberculosis. Sci Rep. 2021 Dec 1;11(1).
15. Twabi HH, Semphere R, Mukoka M, Chiume L, Nzawa R, Feasey HRA, et al. Pattern of abnormalities amongst chest X-rays of adults undergoing computer-assisted digital chest X-ray screening for tuberculosis in Peri-Urban Blantyre, Malawi: A cross-sectional study. Tropical Medicine & International Health. 2021 Nov;26(11):1427–37.
16. Khan FA, Majidulla A, Tavaziva G, Nazish A, Abidi SK, Benedetti A, et al. Chest x-ray analysis with deep learning-based software as a triage test for pulmonary tuberculosis: a prospective study of diagnostic accuracy for culture-confirmed disease. Lancet Digit Health. 2020 Nov 1;2(11):e573–81.
17. Nash M, Kadavigere R, Andrade J, Sukumar CA, Chawla K, Shenoy VP, et al. Deep learning, computer-aided radiography reading for tuberculosis: a diagnostic accuracy study from a tertiary hospital in India. Sci Rep. 2020 Dec 1;10(1).
18. Vo LNQ, Codlin A, Ngo TD, Dao TP, Dong TTT, Mo HTL, et al. Early evaluation of an ultra-portable x-ray system for tuberculosis active case finding. Trop Med Infect Dis. 2021 Sep 1;6(3).
19. Soares TR, Oliveira RD de, Liu YE, Santos A da S, Santos PCP dos, Monte LRS, et al. Evaluation of chest X-ray with automated interpretation algorithms for mass tuberculosis screening in prisons: A cross-sectional study. Lancet Regional Health - Americas. 2023 Jan 1;17.
20. Engle E, Gabrielian A, Long A, Hurt DE, Rosenthal A. Performance of Qure.ai automatic classifiers against a large annotated database of patients with diverse forms of tuberculosis. PLoS One. 2020 Jan 1;15(1).
21. Qin ZZ, Sander MS, Rai B, Titahong CN, Sudrungrot S, Laah SN, et al. Using artificial intelligence to read chest radiographs for tuberculosis detection: A multi-site evaluation of the diagnostic accuracy of three deep learning systems. Sci Rep. 2019 Dec 1;9(1).
22. Qin ZZ, Naheyan T, Ruhwald M, Denkinger CM, Gelaw S, Nash M, et al. A new resource on artificial intelligence powered computer automated detection software products for tuberculosis programmes and implementers. Tuberculosis. 2021 Mar 1;127.
23. Cao XF, Li Y, Xin HN, Zhang HR, Pai M, Gao L. Application of artificial intelligence in digital chest radiography reading for pulmonary tuberculosis screening. Vol. 7, Chronic Diseases and Translational Medicine. KeAi Communications Co.; 2021. p. 35–40.
24. John Janna Health Foundation Suraj Abdulkarim S, Creswell J. Results from TB screening using ultraportable x-ray and articial intelligence in remote populations in northeast Nigeria. 2023; Available from: https://doi.org/10.21203/rs.3.rs-2714909/v1
25. Royal College of Radiology Thailand. Artificial intelligence test project for pulmonary tuberculosis quarantine In the chest picture of the Thai population-Independent evaluation report . 2023.
26. Nanavati Hospital; Symbiosis Center for Medical Image Analysis SIU and DY Patil research Institute. A Twofer for Tuberculosis and Covid-19- third-party evaluation report. 2020.
27. Stop TB Partnership's TB REACH Initiative. Evaluating DeepTek's DxTB (version 20.12) for TB Screening in High HIV/TB Co-Burden Settings: A Comprehensive Assessment Report. 2021.
28. WHO consolidated guidelines on tuberculosis. Module 2: Screening_ Systematic screening for tuberculosis disease.
29. Trevethan R. Sensitivity, Specificity, and Predictive Values: Foundations, Pliabilities, and Pitfalls in Research and Practice. Front Public Health. 2017 Nov 20;5.
30. Dalton BR, Rajakumar I, Langevin A, Ondro C, Sabuda D, Griener TP, et al. Vancomycin area under the curve to minimum inhibitory concentration ratio predicting clinical outcome: a systematic review and meta-analysis with pooled sensitivity and specificity. Clinical Microbiology and Infection. 2020 Apr;26(4):436–46.
31. Hautus MJ. Calculating estimates of sensitivity from group data: Pooled versus averaged estimators. Behavior Research Methods, Instruments, & Computers. 1997 Dec;29(4):556–62.
32. Sharma D, Prinja S, Aggarwal AK, Rajsekar K, Bahuguna P. Development of the Indian Reference Case for undertaking economic evaluation for health technology assessment. The Lancet Regional Health - Southeast Asia. 2023 Sep;16:100241.
33. Bashir S, Kik S V., Ruhwald M, Khan A, Tariq M, Hussain H, et al. Economic analysis of different throughput scenarios and implementation strategies of computer-aided detection software as a screening and triage test for pulmonary TB. PLoS One. 2022 Dec 30;17(12):e0277393.